ERRATA

Page	Line		Change
64	11	from above	change “accepted” to “not rejected”
78	7	from above	change “can be accepted” to “cannot be rejected”
87	2	from below	change “can be accepted” to “cannot be rejected”
98	4	from above	change “cannot be accepted” to “can be rejected”
99	8	from above	change “accepted” to “not rejected”
103	4	from above	change “cannot be accepted” to “can be rejected”
103	6	from below	change “accepted” to “not rejected”
108	1	from above	change “cannot be accepted” to “can be rejected”
121	9	from below	change “cannot be accepted” to “can be rejected”
134	5	from below	change “cannot be accepted” to “can be rejected”

(This errata sheet was submitted to the Thesis Office January 24, 2007 by Ivan Tasic for inclusion with his dissertation)

IMPACT OF RETAILER'S PROMOTIONAL ACTIVITIES

ON CUSTOMER TRAFFIC

A Dissertation

by

IVAN TASIC

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2006

Major Subject: Economics

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Approved by:

Chair of Committee,	Steven N. Wiggins
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ABSTRACT

Impact of Retailer's Promotional Activities on Customer Traffic.

(May 2006)

Ivan Tasic, B.S., University of Belgrade, Serbia;

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Chair of Advisory Committee: Dr. Steven N. Wiggins

The usual theoretical assumption that the retailer's promotional activities serve the purpose of attracting customers into stores lacks empirical verification. The relationship between promotional activity and customer count is examined empirically in just a few studies, and no significantly positive association is found. This dissertation is a comprehensive empirical study of a unique time series cross section dataset, which contains scanner data representing 28 product categories in a large supermarket chain over two and a half year long period. The main result of this dissertation is that retailer's promotional activities are positively related to customer count. Two constructed measures of the promotional activity have a positive significant effect on store traffic that is comparable with the customer count effect of an average holiday. Some 55 percent of the positive long-run promotional activity effect is felt immediately, and the remaining 45 percent is spread over a five week long period. The promotions have prolonged effects that last until the next promotional peak – the next holiday. It is also found that promotional discounts have positive and significant effect on store profit.

To my mother and brother

ACKNOWLEDGMENTS

I would like to thank my committee chair, Dr. Steven N. Wiggins, and my committee members, Dr. Qi Li, Dr. Steven Puller, and Dr. Asghar Zardkoohi for their guidance and support throughout the course of this research.

I thank my family for their endless encouragement, sometimes unspoken, and for their understanding that meant so much. This dissertation would not see the light of day without them.

I am grateful to my colleagues and the department faculty and staff for making my time at Texas A&M University unforgettable. I would like to extend my gratitude to the Serbian community in Bryan/College Station for their support and the great times we had. I have also met many great individuals both in the Russian Orthodox Christian Student Association and the Orthodox Christian Fellowship. Knowing them made me a rich man.

Finally, I thank the James M. Kilts Center, Graduate School of Business, University of Chicago, for making the Dominick’s database available.

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1. INTRODUCTION

The main objective of this dissertation is the identification of the relationship between store traffic and promotional activity. Retail promotional activity is primarily related to sales, which can be defined as temporary price reductions followed by similarly sized price increases. There are numerous studies that assume a strong positive relationship between promotions and customer count. Although this assumption seems reasonable, it has not been empirically confirmed. It is the empirical verification or rejection of this assumption which motivates this work.

Many authors assume that the retailers' promotional activity leads to an increased customer count. It would be nearly impossible to list them all here, but some of the most prominent include the following: Hess and Gerstner (1987), Lal and Matutes (1994), Blattberg, Briesch and Fox (1995), Drèze (1999), and DeGraba (2003). Although the assumption of a positive relationship between promotional activity and store traffic keeps re-appearing in many papers, empirical studies tackling this issue are very scarce. There are only three – Walters and Rinne (1986), Walters and MacKenzie (1988), and Srinivasan, Pauwels, Hanssens and Dekimpe (2004) – that provide some evidence of a very weak relationship. Indeed, given the number of limitations discovered, these authors conclude that this relationship is sufficiently weak to warrant its being considered insignificant.

There are other empirical studies, of course; many of them providing a wealth of

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This dissertation follows the style of *Econometrica*.

information on and rich descriptions of retailers' activities, price behavior and best practices. A very short overview of their main findings is given in the order in which they were published. Hoch, Drèze and Purk (1994) compare two major pricing strategies: (i) the Everyday Low Price (EDLP) strategy in which a retailer charges a constant everyday price with no temporary discount, and (ii) the "Hi-Lo" strategy in which a retailer charges higher prices on a daily basis, but then runs frequent promotions. The first strategy damages profit. Warner and Barsky (1995) find that sales occur more frequently during intensive shopping periods (holidays). Hoch, Kim, Montgomery and Rossi (1995) show that competitive and demographic variables explain up to 67 percent of the variation in store-level price elasticities, with demographic variables having more explanatory power than competitive variables. MacDonald (2000) discovers that data does not support the hypothesis that peak period retail price declines reflect seasonal declines in costs.

Hosken, Matsa, and Reiffen (2001) introduce a notion of the "regular" (modal) price. The product's prices are equal to their modal value at least 50 percent of the time. Most deviations from that price are downwards. Vanhuele and Drèze (2002) conclude that consumers do not possess an accurate knowledge of prices, but they possess a working knowledge of prices that is accurate enough to provide basis for good purchasing decisions. Chevalier, Kashyap, and Rossi (2003) establish the following result: when there is an idiosyncratic demand peak, price decreases, retail margin is lower, wholesale price remains almost constant, or decreases slightly, and advertising increases.

Hosken and Reiffen (2004a) examine the changes in the frequency of sales, and the probabilities of sales in periods of high and low demand. Retailers systematically place some products on sale more often than others. They also find a significant positive relationship between a product's market share and the likelihood of its going on sale. Hosken and Reiffen (2004b) find that the price variation associated with a temporary price reduction represents between 20 percent and 50 percent of the price variation in the category. Srinivasan, Pauwels, Hanssens and Dekimpe (2004) find that price promotions are not beneficial to the retailer and that price promotions resulted in a positive effect on store traffic for 15 percent of the examined brands, while having no impact on the remaining 85 percent. This analysis is limited to subsets of brands, and does not include overall retailer's activity.

Clearly, these empirical studies provide valuable results, but an extensive analysis of the effects of promotional activity on store traffic is simply missing. One possible reason for this could be a lack of data. Even if promotional activity or customer count data exist separately, they are rarely found in one dataset. However, the Dominick's Finer Foods (DFF) database, available on the internet from the James M. Kilts Center, Graduate School of Business, University of Chicago, offers a wealth of information. This data was used in several well known analyses, one of which initiated my interest in the subject – Chevalier, Kashyap, and Rossi (2003). There are actually two separate datasets – one containing daily traffic data, and another containing weekly sales data for the same group of stores.

Although this dataset has been available for quite a while, no previous attempt has been made to analyze customer traffic data and its possible association with promotional activities. There are no ready-to-use promotional activity variables. These had to be constructed, and that represented a major challenge. Extensive data processing is performed in order to extract and adequately aggregate needed data. Store traffic data is relatively simple to extract and aggregate, but the construction of the promotional variables is quite demanding.

Another possible reason for the absence of an empirical study is the size of this dataset. It is not hardware limitations that make this analysis nearly impossible, but rather the software limitations which were reached during data processing. A lot of creativity in finding workarounds is needed, and this research has definitely been a learning experience in processing large datasets. A great deal of computer code is produced, tested and checked. It is expected that this code will be useful in other applications.

The processed data is of the time-series cross-sectional (TSCS) form. There are 67 stores and 132 weeks of data available. This particular data form is very specific, because the time dimension is greater than the cross sectional one. The data set resembles (macro) panel data, so that many methods used for panel data analysis are applied. However, the time series cross section form means that the asymptotics will be drawn from the time series side of the data, and not the cross section, and this has strong implications for the choice of estimators.

Two major models are developed – static and dynamic. Before any analysis is done, the data must be checked for several potential problems which, if found, would invalidate any obtained results. The first procedure involves checking the data for any form of non-stationarity, i.e. unit-roots. Analysis shows that unit roots are not present. The next step requires a selection of the right family of estimators, based on several tests. Simply, the decision to pool or not to pool the data is made based on the Chow test. Other studies and theories suggest that pooling is not a viable option, so other forms of random or fixed effects models are considered, after the Hausman test of systematic differences in coefficients' values has been performed using the augmented regression technique.

Once these basic tests are performed, a specification search process takes place. During this process, the determination of which variables belong to the static model is made. Several measures of fit are used – the R-square adjusted, the root mean square error, the Akaike information criterion, and the Bayesian Schwarz information criterion, but specification decisions are based primarily on the last one.

After the first regressions are run, a very detailed diagnostic procedure is applied in order to detect any possible departures from the model/estimator assumptions, which, if found, could completely invalidate the results and inference. A search for groupwise heteroskedasticity (the Modified Wald test), contemporaneous correlation across panels (the Breusch-Pagan LM test), and serial correlation in idiosyncratic error terms (the Wooldridge test for autocorrelation) is performed. Some standard software packages cannot perform many of these tests on this particular data, so some of the tests' codes had to be written. Since groupwise heteroskedasticity and contemporaneous correlation across panels are diagnosed, an alternative estimator must be used instead of the standard within groups estimator, and that was the least squares dummy variable panel corrected standard errors estimator.

The results of the static model indicate that promotional activities are positively related to store traffic. It is questionable whether this effect can be considered weak or strong, but it is significant without a doubt. This static model was developed as an intermediate phase towards creating a more complex and challenging dynamic model.

The dynamic models impose additional difficulties in the estimation process. These could present great econometric challenges. Including the lagged dependent variables, and finding the optimal number of lags, bring many estimation difficulties that must be addressed very carefully. The data used in this dissertation may potenitially confirm the dynamic panels theory and confront at least two estimators whose use is justified for such data. The Arellano-Bond estimator is used as a primary estimator that is intended for the dynamic panel data. Since the time series dimension is large, and the instrument matrix used in the analysis grows rapidly, this estimator reached the limits of both software and hardware, so some limits had to be imposed, as is the usual practice. A sequence of results obtained using this estimator are put together and compared for the different (increasing) number of instruments used. It can be shown that the results from the Arellano-Bond estimator converge to those of the Prais-Winsten panel corrected standard errors estimator. The theory says (Alvarez and Arellano (2003)) that both estimators are consistent when T/N tends to a constant between 0 and 2, which is the case with the used data.

Finally, the dynamic coefficients provide information on the long-term effects of promotions. This long-term effect is not measured in months or years, but weeks. Stores promote from one to another peak shopping period. The long-term coefficients are based on the theoretical models. A Wald-type test of smooth nonlinear hypothesis is constructed and examined, and the standard errors calculated and presented. The results show that promotions do have a positive effect on store traffic. Roughly 55 percent of the long-run effect is felt immediately, but the remaining 45 percent is spread over a five week long period. The promotions have prolonged effects that last until the next promotional peak – the next holiday.

Promotional discounts have a positive effect on store profit. This result is another significant finding. It implies that for every dollar of promotional discounts, net revenue increases by 8 cents. Although the average acquisition cost method is used to compile the profit margins in the dataset, high turnover rates in the supermarket industry ensure that this result is reasonable.

The remainder of this dissertation is organized as follows. Section 2 provides a thorough classification and overview of the literature. Section 3 contains information on the data sources, detailed description of the raw and processed data, the variables construction process, and primary analysis of the most characteristic features found in the data. Section 4 shows how the static model was developed. Section 5 presents the estimation results of the static model. The dynamic model is developed in Section 6, and the estimation results of the dynamic model are what constitutes Section 7. Section 8 introduces some profitability issues. Section 9 offers some final thoughts and conclusions.

2. LITERATURE REVIEW

The interest for advertising expenditures and their effects on consumer behavior as well as firms' operations has always been notable. This is unsurprising given that advertising expenditures represent considerable sums in both absolute and relative terms. Knowing their effects on a particular firm's market success helps direct them from less profitable to more profitable uses, which is at the very core of economics.

To objectively present the vast literature on advertising is an ambitious task. There are many models, surveys, and studies, which evolved in countless journal articles and books. Nevertheless, for the purpose of this work only a part of that literature will be surveyed, with the hope that some major related work is not overlooked or omitted. The effect of price promotions on sales is the primary area of interest. Sales are temporary price reductions followed by similarly sized price increases. There are many theories and models that attempt to explain why sales happen. Theoretical models can be organized in three major groups based on the reasons why sales happen: (i) to price discriminate; (ii) to build store traffic; and (iii) to build store image. When it comes to empirical insights, two points of view are presented: (i) a practitioners' category management technique on one side; and (ii) an abundant set of results of various empirical research studies on the other.

2.1. Price Discrimination

The early models of sales dealt with single-product retailers. Varian (1980) examines the rationale of price dispersion by means of sales. He shows that monopolistically competitive stores randomize prices in an attempt to price discriminate between informed and uninformed consumers[1]. He assumes that uninformed customers choose a store at random and buy as long as the price is below their reservation price, while informed customers know the whole distribution of prices and buy from the store with the lowest price. Sales are the result of the static imperfect competition between retailers who compete for informed consumers (those who read advertised sale prices in weekly newspaper). There are two strong assumptions in this model: (i) prices are drawn from a continuous distribution with no point masses; and (ii) price is always greater than marginal cost. These assumptions will prove to be major drawbacks of Varian's model.

Conlisk, Gerstner and Sobel (1984) present another model that serves as a building block for future work. They show that a monopoly retailer holds periodic sales as a means of temporal price discrimination against impatient, high-value customers. If a retailer charges a high price, low-value customers do not make a purchase. As the number of dissatisfied low-value customers grows, it becomes profitable to lower prices sufficiently to sell to the large group of low-value customers that have accumulated, resulting in volume increases on a sale day. Since all "low-willingness" consumers buy on a sale day, the price rises immediately after a sale day.

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[1] Varian (1980, p. 652) observes that "this is only one aspect of real world sales behavior. Other reasons for sales behavior might include inventory costs, cyclical fluctuations in costs or demand, loss leader behavior, advertising behavior, and so on. The theoretical examination of these motives is left for future work." Future work took all these different directions, so that Varian's suggestions fully realized.

Sobel (1984) introduces a multiple-retailer (oligopoly) inter-temporal price discrimination model. In most periods the price is high and only consumers with high reservation price make a purchase, but periodically it is attractive to lower the price and sell to a large group of consumers with low reservation prices. An oligopolistic market differs considerably from a monopolistic one: Is it preferable to (always) sell to the group of loyal customers at a high price, or cut prices and sell to both - these customers and accumulated non-loyal consumers before a rival does? Sobel raises several very important issues that will be addressed years later: (i) increased number of competing retailers has the effect of greater frequency and depth of sales; (ii) the expected price decreases as the time from last sale increases; (iii) certain sales are traditional and so well publicized that it is difficult to justify them as devices to separate informed from uninformed consumers. As these findings opened many opportunities for further research, Sobel's contribution cannot be overemphasized.

Pesendorfer (2002) builds on Sobel (1984), and introduces a concept of inventorying to explain pricing behavior in supermarkets. If the current price is above the reservation price of the low-value customers, they consume a good from their inventory, whereas high-value customers do not stock. Whenever the price falls below their reservation price, low-value consumers make a purchase. This model implies that a store's decision to conduct a sale is a function of the wholesale price and the duration of time since the last sale in that store and other stores. This model fails to explain discounts for perishable goods that are frequently purchased but not inventoried. Sobel and Pesendorfer combine Varian's (1980) and Conlisk, Gerstner and Sobel's (1984) models, attempting to bring together price discrimination and competition elements of both.

Hosken and Reiffen (2001) develop a two-product retailers model. Here a nonperishable good is the one with price discriminative capability, and a perishable good cannot be used for price discrimination. Retailers use one product to compete with rivals, while reserving the other for discriminating between high-value and low-value consumers. They challenge Varian's continuous price distributions by indicating mass points (modal prices) in price distributions. In addition, consumers buy an array of goods each time they visit a store. It follows that retailers compete for customers by attempting to offer the most attractive set of prices. Their model predicts that price changes of non-perishables and perishables are negatively correlated. Hosken and Reiffen count this as evidence suggesting that price discrimination by inter-temporal price changes is one function served by sales in the food retailing industry.

2.2. Loss Leader Pricing

Another large class of models relies on loss leader approach. Loss leader is a good that's priced at or below cost. It is used to attract customers into the store so that other products with higher margins are also purchased, and the losses incurred by loss leaders could be offset. Loss leaders are heavily advertised in the local newspapers.

The first formal loss leader model was developed by Hess and Gerstner (1987). They define "impulse goods" as products bought on sight without price comparisons across stores, and "shopping goods" as those used to determine which store to visit. Stores sell a selection of "impulse goods" and only one "shopping good", and fully informed consumers are assumed to visit only one store each period. They check effects of loss leader pricing and rain-check policies on stores' profits and market outcomes. Hess and Gerstner show that stores find it of interest to price the shopping good below marginal cost to attract consumers into the store, and make profits through the purchase of impulse goods. Some stores limit the purchase of leader items to one per customer, while others run out of the leader products, and offer rain checks to frustrated customers. Rain checks are introduced to enhance the effect of the loss leader, because they bring customers to the store a second time.

One of the most frequently cited papers on loss leader pricing is written by Lal and Matutes (1994). They are the first to explicitly introduce advertising as a necessary element into the loss leader pricing strategy model. They develop a duopoly model in which each firm sells two products and consumers are uninformed about prices unless they are advertised. The role of advertising is that of a commitment device. Loss leader goods do attract consumers into the store even if they are rational and expect to pay very high prices for unadvertised goods[2]. Lal and Matutes relax the assumption of impulse goods, allowing consumers to decide which store to visit based on the surplus derived from the purchase of an assortment of goods. This work shows that the interplay between imperfect information, rational expectations, and multiproduct competition can lead to an equilibrium where firms offer and advertise loss leaders to compete for store traffic. If the willingness to pay is sufficiently high, firms can extract a large consumer surplus from the unadvertised good.

Lal and Matutes later (p. 363) relax the assumption that consumers' willingness to pay is the same for both products. Only the lower reservation price good is used as the loss leader and firms' profits and store traffic remain the same whether or not loss leaders are offered in equilibrium. This provides a rationale for the cases in which loss leaders do not fulfill their usually assumed purpose. There are some empirical findings along these lines to be addressed. They do emphasize (p. 363) that "this does not contradict the fact that when we focus on a specific equilibrium, firms offer loss leaders to increase store traffic and profits." The effectiveness of the loss leader pricing strategy is found in the relationship between the willingness to pay and the cost of advertising, on one side, and the opportunity cost of shopping on the other. If the former are high relative to the latter, profits and traffic can be expected to rise.

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[2] Lal and Matutes (1994, p. 357) introduce and describe the role of advertising: "Furthermore, since consumer expectations are rational, advertising is not informative about prices. Instead, it is a means whereby stores guarantee consumers a positive surplus so as to make the shopping trip worthwhile". If a firm does not advertise, it gets zero customers and therefore zero profits.

Clearly, loss leader pricing exists, and is used in practice, but its effects on overall store profitability and traffic are assumed to be positive, although this is not a proven fact. One has to exercise extreme caution when reading through the literature, and not take anything for granted. A good example of inconsequential work is that of Blattberg, Briesch, and Fox (1995). They claim that four papers[3] provide evidence of the positive effect of advertised promotions on store traffic. This is far from true. Only two of these articles very cautiously suggest that there is some weak or insignificant effect at best, and summaries of these articles follow. The other two papers provide store-switching models with results that do not provide the strong implications for store traffic for which they are cited. Rather, they relate promotions to the relative category sales, which is not a measure of store traffic.

Walters and Rinne (1986) check the effects of ten loss leader portfolios as well as double coupon promotions on three stores' sales, traffic and profitability. This is the result (p. 262): "... only two portfolios (#3 and #6 in store #1) had a significant impact on store traffic." Another result is also significant (p. 263): "Loss leaders and double coupon promotions perform the important task of helping create and nurture a price-competitive image among the store's regular and potential customers. (...) The results of the study also suggest that much of the response to loss leaders and double coupon promotions comes from the store's present customers and not from 'new' customers attracted to the store because of the promotions."

[3] The articles in question are: (i) Walters and Rinne (1986); (ii) Walters and MacKenzie (1988); (iii) Kumar, V., and R. P. Leone (1988): "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution," *Journal of Marketing Research*, 25, 178-185; (iv) Grover, R., and V. Srinivasan (1992): "Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments," *Journal of Marketing Research*, 29, 76-89.

Walters and MacKenzie (1988) develop a series of hypotheses and empirically investigate loss leader pricing, i.e. effects of price promotions on grocery store sales, traffic and profit. They find that loss leaders do not affect store profit, and that only one of the eight loss leader categories significantly influence store traffic. They show that firms make the same profit whether or not they use loss leader pricing. They exercise caution, stating that promotions may function in ways the data are not capable of detecting, and they conclude that their results provide little support for the notion that price promotions stimulate sales of non-promoted merchandise at the store-wide level.

The work by Chevalier, Kashyap, and Rossi (2003) embraces several theories and tries to empirically distinguish between them. These competing theories of countercyclical pricing state: (i) prices fall if the consumers are more “price sensitive” during high purchase periods (due to increased search); (ii) prices fall if collusive behavior breaks down during high purchase periods; (iii) prices of some items fall if advertising is costly and consumers are imperfectly informed. When there is an idiosyncratic demand peak price decreases, retail margin is lower, wholesale price does not significantly change, or slightly decreases, and there is an increase in advertising. They confirm the existence of advertising, as suggested by Lal and Matutes (1994), selecting the third (loss leader) model as applicable. Chevalier, Kashyap and Rossi do not mention store traffic in their work.

The only work that explicitly addresses customer count empirically is that of Walters and MacKenzie (1988). Later studies usually avoid mentioning store traffic, and doing so reduced their chance for publication. One of these is the study of the relation between loss leaders and cherry picking by Drèze (1999). He shows that cherry picking is not an undesirable behavior, and that retailers, by allowing it, can increase profits through both offering shallow discounts, and avoiding direct competition on promotions. More importantly, Drèze (1999, p. 30) empirically confirms several aspects of loss leader pricing strategy, but recommends the following one: “loss leaders do not generate incremental traffic, they only prevent store traffic from decreasing.” This leads to the following question and response: “If loss leaders have no spillover effects on other categories, why do retailers keep selling turkeys below cost on Thanksgiving? Because if they did not sell turkeys at the lowest possible price, they would lose their core customers for that week.”

DeGraba (2003) sheds more light on loss leader pricing. He suggests that an important consideration for choosing a product as a “loss leader” is its purchase primarily by high profit (large volume) producing customers. DeGraba states: “All else equal the larger the basket of goods in which a good is purchased, the lower should be the mark up on it” (p. 16). Popularity and frequent purchase of a product are not enough to make it a loss leader. Namely, turkey at Thanksgiving is a loss leader, but candy on Valentine’s Day is not. People who purchase turkey on average purchase more units of other goods, while the candy is probably the only item purchased. Stores offer discounts on turkey prices around Thanksgiving, but there is no discount on candy prices around Valentine’s Day.

2.3. Store Image

This survey of the literature suggests that just a handful of models and articles addressed explicitly the issue of store traffic, and the effects of promotions on the latter were mild if any. Knowing that considerable sums of money are spent toward promotions, could stores have other goals than immediate traffic increase? Consumers' price perceptions and the image stores have in their eyes have been theoretically examined. Nevertheless these two phenomena cannot easily be empirically verified, which is why the reach of the models has been limited, and remains largely theoretical.

Brown (1969) examines relationships between non-price store characteristics and actual price level perceptions. If the consumer believes that certain kinds of stores have either high or low prices, she may infer specific stores' general level of prices from this relationship without even investigating prices. Consumers perceive that plenty of advertising is associated with low prices. In addition, loss leaders are believed by consumers to be associated with high volume operations, and these are linked to low prices. Consequently, loss leaders are indirectly associated with low prices (through both advertising and large volume operations). A store image is not determined by one characteristic alone[4]. These characteristics interact, sometimes reinforcing each other, sometimes offsetting each other.

An oligopoly model developed by Friedman (1983, p. 466) emphasizes inter-temporal effects of advertising: "A given ad is likely to have a greater effect the more the firm has advertised in the past. Past advertising increases the awareness of potential

[4] Store characteristics examined include: new (store), untidiness, large shopping center, lots of advertising, wide assortment, loss leaders, trading stamps, expensive interior, open late, extra services, small.

customers of the firm and makes them more likely both to read the firm's ads and to buy the firm's products. Thus, an advertisement made today has an effect both today and into the future, though the effect of today's ad should diminish over time."

Arnold, Oum and Tigert (1983) examine the determinants of retail patronage through a series of analyses of covariance of multinomial logit parameters. Parameters are estimated from random samples drawn from six North American and European markets over a seven-year period. This very frequently cited work provides the following conclusions (p. 156): "... location, price, assortment, fast checkout, friendly and courteous service, meat, weekly specials, and pleasant shopping environment are critical determinants of patronage. Location and price, in particular, appear to dominate the choice process." Along similar lines, Bliss (1995, p. 391) writes: "People trust certain shops. Sometimes this is a question of quality, but sometimes what is trusted is a pricing policy. The consumer lacks information concerning prices in all shops but trusts a certain shop to give good value."

Feichtinger, Luhmer, and Sorger (1988, p. 192) provide the following insight: "... many consumers do not worry about the single purchase of convenience goods; rather they adopt buying habits in order to get the best value for their money and effort in the long run. The store price image mirrors these buying habits." They explain that purchase decisions on convenience goods are typically made in two stages. First, the customer decides which store to visit, and then once in that store, which items to buy. The latter decision can be based on observed prices, but the first one will depend on past experience, advertising, and word of mouth information. A company may invest in its image by offering low prices. Heavy advertising is profitable only after the image has been improved. Low prices for advertised items will be better accepted as a signal of a low overall price level, if supported by a favorable price image.

Feichtinger, Luhmer, and Sorger emphasize the following (p. 189): “The store’s advertising and price image share in the role of drawing customers into the store. The effect of prices, however is twofold: first they determine the sales receipts from the customers in the store, second they govern the evolution of the store price image. In the case of convenience items, the prices that maximize sales receipts in the short run will lead to an unfavorable image in the long run…” Image creation is achieved through pricing. Once a favorable image is established, the credibility of advertising is enhanced, and increased advertising follows.

Hoch, Drèze and Purk (1994) compare two major pricing strategies: (i) The everyday Low Price (EDLP) strategy in which a retailer charges a constant everyday price with no temporary discount; (ii) The “Hi-Lo” strategy in which a retailer charges higher prices on an everyday basis, but then runs frequent promotions in which prices are temporarily lowered below the EDLP level. EDLP is simple and consistent, increasing the chances of establishing a low price image through advertising. Many Hi-Lo retailers believe that aggressive temporary price reductions help to sustain a low price image. In executing any pricing strategy, firms need to consider the likely impact on two customer sectors: “installed base” (current users) and “opportunity” (nonusers – potential for growth).

Simester (1995) provides a signaling model in which a store can use its advertised price to signal its cost type (and the price of its unadvertised product). He assumes that customers do not know the prices of all products at each store but rely instead on an overall price image for the store. Although stores may charge the same advertised price, they could charge different prices for unadvertised products. One of the results Simester obtains is that low-cost stores reduce their advertised prices in order to protect their low cost image.

All these cited studies on price image do not “require” any specific price knowledge. Consumers do not decide which store to visit or what items to buy based on very accurate memorization of prices, or on any kind of analysis prior to visiting a store. In a way they “feel” the market. An empirical study by Vanhuele and Drèze (2002) provides a useful insight into consumers’ price knowledge. They conclude that consumers do not possess an accurate knowledge of prices, but rather possess a working knowledge of prices that is accurate enough to make good purchase decisions.

2.4. Category Management

Following the definition of Nielsen Marketing Research (1992, p. 9), "category management is a process that involves managing product categories as business units and customizing them on a store-by-store basis to satisfy customer needs. Rooted in the belief that today's new-product explosion has made strategic management by item too impractical and strategic management by department too unfocused, category management transforms retail 'buyers' and manufacturer 'sellers' into entrepreneurs, each responsible for a small business within a large enterprise." This handout continues to provide advice for retailers on the ways categories should be established, as well as what purposes they should serve (pp. 33-35):

> "The way you define a category might differ from the way a manufacturer or market research company sees it, and the way your customers perceive it might be something else entirely. You should collect all of these opinions, but give the most weight to customers' perceptions, which can be determined by analyzing market research data provided by third parties. A good rule of thumb is that products that are substituted for each other should be grouped in the same category. (...) As the definition of each category comes into focus, make sure you identify important subcategories within each category. These smaller product groupings often behave much differently than the rest of a category and can greatly influence its overall performance. (...)
>
> Ask yourself what strategic marketing role each category is best suited to play. Is it an image enhancer? A traffic or sales builder? A profit builder? (...) Once you have determined these facts and identified a strategic role for each category, you should

> establish sales, profit and market-share objectives for each category. Achieving these goals is the job of the category manager."

There has been a lot of controversy regarding whether or not category management fulfilled the tasks it was given. A lot of research was generated based on the assumption that retail stores operate almost exclusively in category management setup.

Chintagunta (2002) checks if a retailer chain follows a simple pricing rule. The main misperception found in the literature is that retailers charge an identical markup or margin across all brands in a category. He presents empirical evidence that this is not the case, because markups as well as margins vary, and they are not correlated. Whatever is the truth about category management, many retail chains use software that helps them make comparisons with other retailers, create planograms, and take into account demographics when creating categories as separate business units.

Since access to the records of business practice of retailers is very limited, the only available tool one can use in research is a series of indirect conclusions drawn from the available data. All available, known, and relevant empirical work related to the promotional activity has been collected and presented in the next few paragraphs. These also represent empirical tests of the three groups of theories described above.

2.5. Empirical Insights

It is evident that until recently there has been a dearth of empirical literature related to the retail markets. Researchers did not have data with which to work, and many conclusions were consequently descriptive in nature, based on assumptions and common sense. Since the mid 1990s, this area of research has gained momentum, and the current understanding of the processes in this industry is somewhat better. The first successful attempt to enter the area of empirically examining what various theories have been suggesting is the work of Warner and Barsky (1995). After implying that economists have written little about price markdowns, they point out the following (p. 321): "... there are a few if any well-established empirical principles that would provide a basis for analyzing the temporal and spatial patterns of markups and subsequent markdowns in retail product markets in any given set of circumstances."

After collecting and processing data[5], the authors deduce that there is yet another motive for sales. Namely, weekend and holiday sales are characterized by a high intensity of shopping activity, and the search for the lowest price takes place more efficiently. Search and travel costs can be partly shared between multiple items purchased during those periods. In their own words (p. 324): "Because consumers are more vigilant and better informed in the high demand states, individual retailers perceive their demand to be more elastic in such periods. The optimal markup of price over marginal cost is thus lower, and the market achieves an outcome closer to that of perfect competition". Warner and Barsky were the first to empirically inspect weekly and

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[5] They examine daily prices of eight goods over a four month period, collected from seventeen stores. They observe only prices, not the volumes purchased.

seasonal price patterns, as well as frequency of price markdowns. Sales occur more frequently during intensive shopping periods.

Using weekly scanner data, Hoch, Kim, Montgomery and Rossi (1995) provide a comprehensive empirical study[6] of the determinants of store-level price elasticities. They show that competitive and demographic variables explain up to 67 percent of the variation in store-level price elasticities, with demographic variables having more explanatory power than competitive variables. The whole analysis is based on one of the major retail chains in the Chicago area - Dominick's Finer Foods. The stores are assigned to one of three pricing zones and the pricing is mainly driven by competition, not demographic factors. Everyday prices are dictated by zones, and promotional prices are determined in a uniform manner across the chain. Different elasticities arise from the different quantity responses that result from diverse neighborhoods.

Since the results of this study generated a lot of discussion and follow-up studies, their summary is provided here (p. 28): (i) More educated consumers have higher opportunity costs and so devote less attention to shopping and therefore are less price sensitive; (ii) Large families spend more of their disposable income on grocery products and therefore spend more time shopping to garner their increased returns to search. They are also more price sensitive; (iii) Households with larger, more expensive homes have fewer income constraints so that they are less price sensitive; (iv) Black and Hispanic consumers are more price sensitive; (v) Store volume relative to the competition is important, suggesting that consumers self-select for location and convenience or price

[6] They combine data from several sources: Dominick's Finer Foods, Information Resources Inc, and Market Metrics.

and assortment; (vi) Distance from the competition also matters. Isolated stores display less price sensitivity than store located close to their competitors. Distance increases shopping costs.

As the temporal price variation was getting more attention in the literature, a need for a deeper look into the structure of prices and processes therein arose. MacDonald (2000, p. 38) recognizes seasonal demand patterns, but investigates further and provides a useful result: “The data do not support the hypothesis that peak period retail price declines reflect seasonal declines in costs.” This is how retail margins came into focus of another, earlier cited study - Chevalier, Kashyap, and Rossi (2003). They show that prices decrease because retail margins shrink. At the same time, wholesale prices either do not change or only slightly decrease.

Retail price dynamics have several empirical regularities explained in a fruitful work of Hosken, Matsa, and Reiffen (2001)[7]. Stores seem to have a “regular” (modal) price. The products’ prices are equal to their modal value at least 50 percent of the time. Most deviations from that price are downwards. Within each category, the same items are regularly put on sale, while other items are rarely, if ever, put on sale. The probability of a sale of an item appears to be the greatest when the demand for that item is highest. In addition, more popular items are more likely to be put on sale. This means that if an item has had a previous history of being on sale, chances are it will be put on sale again. Hosken, Matsa, and Reiffen raised many important questions, some of which were answered in their subsequent work.

[7] They base their observations on a large nonpublic dataset provided by the Bureau of Labor Statistics. This dataset includes 20 categories and thirty US metro areas over a ten year period (1988-1997).

Perishable goods' dynamic price patterns are generally neglected in the literature. This is why Hosken and Reiffen (2001, p. 135) concentrate on it. Based on the A.C. Nielsen dataset[8], they show that prices for the non-perishable and the perishable good seem to be negatively correlated. When price changes occur they are larger in magnitude for the non-perishable good. They also re-confirm a result found in another dataset[9] which suggests that retail price changes are not primarily driven by changes in wholesale prices.

All of these studies suggest that retail margin reductions play an important role in the observed variation in retail prices. Hosken and Reiffen (2004a) look at additional evidence implying that retail margin reductions can be associated with increased demand for specific products. They examine the changes in the frequency of sale, and the probabilities of sale in periods of high and low demand. What they find is that retailers are more likely to put items on sale during periods of high demand. This result has a further implication (p. 163): "... average prices are lower in period of high demand because popular items become better candidates for retailers' sales during these periods." Hosken and Reiffen also find strong evidence that there is heterogeneity across products in the likelihood of having a sale. Retailers systematically place some products on sale more often than others. Finally, they find a significant positive relationship between a product's market share and the likelihood that it goes on sale. In other words (p. 168): "... the items retailers choose to put on sale are those with the broadest appeal to consumers."

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[8] Also known as ERIM dataset.
[9] MacDonald (2000).

Hosken and Reiffen (2004b) conclude a whole series of studies which closely examines the price variation and frequency of sales. They find that the price variation associated with temporary price reduction represents between 20 and 50 percent of the price variation in the category, despite the fact that temporary reductions account for fewer than 8 percent of all observations. Although some retail pricing dynamics have been explained, more needs to be done (p. 145): "... some aspects of the motivation for retail price changes remain unexplained."

The latest empirical investigation of promotional activity confirms some of the results obtained in earlier studies. Srinivasan, Pauwels, Hanssens and Dekimpe (2004) perform a vector autoregressive (VAR) analysis of promotional effects on manufacturers' and retailers' performance. They find that price promotions are not beneficial to the retailer. The result that is of interest here is that there is a positive effect of price promotions on store traffic for 15 percent of examined brands[10], while the remaining 85 percent have no impact. Out of ten brands that are effective in generating traffic, only four have positive impact on store revenues. The authors conclude the following (p. 624): "This could be because the additional traffic generated by loss leader promotions consists mainly of cherry-picking consumers." There is nothing in the article supportive of the notion that top selling brands are loss leaders.

[10] Authors use three best selling brands in each of 21 categories they examine. They have a total of 63 brands used in the analysis. It is worth noting that each category has tens and sometimes hundreds of brands, so this analysis' results should be read with a lot of caution. Another call for concern would be that the authors do not report how big the effects are. They just count ten brands with positive effect, which could be as high as 1 or 100 additional consumers, and we do not know this. For the record, weekly store traffic is measured in thousands of consumers.

Although the effects of price promotions on store traffic are assumed to be positive in almost every work that mentions consumer traffic, there are only three empirical studies[11] that provide some evidence of a very weak relationship. Given all the limitations the authors of these studies warn about, they conclude that this relationship is so weak that it could be considered insignificant. Why, then, is it so often assumed?

[11] Walters and Rinne (1986); Walters and MacKenzie (1988); Srinivasan, Pauwels, Hanssens and Dekimpe (2004).

3. DATA

3.1. Raw Data Description

The key data used in the analysis is obtained from the Dominick's Finer Foods (DFF) database, available on the internet[1] from the James M. Kilts Center, Graduate School of Business, University of Chicago. There are two major groups of data from this source: general files and category specific files.

General files are: (i) the customer count file; and (ii) the demographics file. The customer count file includes daily, store-specific, information about in-store traffic. This data refers to the number of customers visiting the store and purchasing something. It also includes total dollar sales and total dollar value of coupons redeemed by DFF defined department. These figures are compiled from the register/scanner receipts. The demographics file consists of store-specific demographic data. The data originally comes from the 1990 US Government Census for the Chicago metropolitan area. Market Metrics processed this data to generate a static demographic profile for each of the DFF stores.

Category specific files are: (i) UPC files; and (ii) "movement" files. A UPC file contains one record for each UPC in a category. It includes information about product name, package size, commodity code, etc. Movement files contain weekly sales data for each UPC in each store for 7 and a half years (400 weeks). They include data on price, quantity sold, profit margin and deal code. Nevertheless, only two and a half years of

[1] Dominick's Database, the James M. Kilts Center, Graduate School of Business, University of Chicago, <http://gsbwww.uchicago.edu/kilts/research/db/dominicks> (Accessed on: October 22, 2003).

data are used, and the reasons for that will quickly become clear.

Table 3.1 provides a snapshot of one movement file. It provides information about Coors Beer, 24-pack of 12 oz cans (UPC = 7199011600), sold in the store number 71. The ‘qty’ variable indicates the size of the bundle (e.g. 1), ‘price’ reflects the total price of the bundle (e.g. $9.99 for week 156), but ‘move’ shows the quantity of the actual item sold, not the number of bundles[2]. In order to compute total dollar sales, one should perform the following calculation: Dollar Sales = PRICE * MOVE / QTY.

Table 3.1. Snapshot of a Movement File

STORE	UPC	WEEK	MOVE	QTY	PRICE	SALE	PROFIT	OK
...	...	...	...	...	...		...	...
71	7199011600	149	3	1	11.99		1.16	1
71	7199011600	150	9	1	10.99	B	7.82	1
71	7199011600	151	2	1	10.99	B	7.82	1
71	7199011600	152	0	1	0		0	1
71	7199011600	153	1	1	11.99		1.16	1
71	7199011600	154	0	1	0		0	1
71	7199011600	155	1	1	11.99		1.16	1
71	7199011600	156	18	1	9.99	S	18.61	1
71	7199011600	157	5	1	10.99	B	7.82	1
71	7199011600	158	1	1	11.99		1.16	1
...	...	...	...	...	...		...	...
71	7199011600	198	3	1	11.99		1.16	1
71	7199011600	199	4	1	11.99		1.16	1
71	7199011600	200	80	1	8.99	S	-31.81	1
71	7199011600	201	27	1	9.99	S	-18.61	1
71	7199011600	202	2	1	11.99		1.16	1
71	7199011600	203	3	1	11.99		1.16	1

[2] If ‘qty’ (size of a bundle) was 4, and ‘move’ was 20, this would give a sale of 5 bundles at a given price per bundle.

Another important aspect of this dataset is the flag ‘sale’. It indicates that a particular UPC was promoted in a given week. A code ‘B’ indicates a Bonus Buy (In-Store Display), ‘C’ indicates a Coupon, and ‘S’ indicates a Store Special (Feature Ad). The profit margin is given as a percentage that DFF makes on the sale of a UPC. A profit of 19 means that DFF makes 19 cents on the dollar for each item sold. It is also possible to sell at a loss as weeks 200 and 201 show. Flag ‘OK’ shows if data is valid or suspect. All entries which had zero value were excluded from the analysis.

Wholesale price is recoverable from the margin[3], but it is possible to obtain only the average acquisition cost[4], and not the replacement cost, which limits the usage of this part of data. There are at least two reasons why the average acquisition cost is not an acceptable approximation of the replacement cost. First, the adjustment to wholesale price change could be very slow. Replacement cost would be low after wholesale price decreased, but this would not show in average acquisition cost if the higher priced inventory depletes slowly. Second, if suppliers inform stores about a temporary price reduction, they could completely deplete their stock, and then overstock at a lower price. Average acquisition cost would decrease very quickly to a lower level, and it would stay there until this newly acquired inventory is sold, despite the replacement cost being possibly high again. The only remaining “hope” for the usage of this data comes from high inventory turnover rates in the supermarket industry.

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[3] Wholesale price = ((100 – Margin)/100) * Price

[4] $\text{AAC}_{t+1} = \dfrac{(\text{Inventory bought}_t \cdot \text{Price Paid}_t) + (\text{Inventory}_{\text{end of } t-1} - \text{Sales}_t) \cdot \text{AAC}_t}{\text{Inventory}_{\text{end of } t}}$

Chintagunta (2002, p. 142) clarifies the fact that wholesale prices include off-invoice promotions and money given for feature advertisements and special displays, but do not include brand development funds (revenue based) or slotting fees (lump sum payment to retailer). Also wholesale prices do not include any overhead costs.

The time span is two and a half years, or 132 weeks, and this is considerably shorter than the seven and a half years of available data. The reasons for using just a third of the available data are threefold. First, Chintagunta (2002, p. 142) explains that wholesale prices do not include brand development funds (revenue based) or slotting fees (lump sum payment to retailer). These payments are never reflected in the data, but their incidence varies considerably over time. Following recent work by Srinivasan, Pauwels, Hanssens, and Dekimpe (2004, p. 621), the sample period is terminated in 1994 because in subsequent years manufacturers made extensive use of "pay-for-performance" price promotions. From the perspective of a customer it should not matter who bears the cost of promotion – retailer or manufacturer – but retailer's overall "promotional" behavior seems to have changed. It is not possible to effectively recognize and detect the process that drives retailer's promotional activity in the case of extensive manufacturers' support. Some economically meaningful relationships become non-existent when weeks from 1994 and beyond are included in the analysis.

Another important constraint that was taken into consideration was the number of days when stores had not reported their customer traffic. Significant lack of traffic data exists for weeks 1 through 93, and beyond week 225, which is coincidentally the last week of 1993. The number of missing days is negligible for weeks 94 through 225. Even in this case it is possible to introduce an adjustment – (sample) mean correction – to remedy the problem, but the results of the analysis showed one half of a percent difference in mean traffic between corrected and uncorrected traffic series. Finally, seven categories have no data reported for the first 100 weeks, which is one quarter of the categories investigated. Consequently, the sample period starts at the end of June of 1991 because of the missing data problem (both price and traffic), but finishes at the end of 1993 for two reasons – because of lack of traffic data, and because data becomes contaminated by the lack of reflection of considerable manufacturers' payments.

Table 3.2 shows basic characteristics of the raw data. It presents all 29 categories in detail: number of UPCs available, total number of observations, as well as shares of three promotional types in total number of observations. There are 29 categories of products, but only 28 are used in the analysis. Cigarettes are excluded because they were not promoted, which is of primary interest.

Clearly, coupons had a very limited role in total promotional activity. It is not clear if the coupon data are missing as stated by Levy, Muller, Dutta, and Bergen (2005), because they are not completely absent, as can be seen in Table 3.2. Coupons are offered by manufacturers, not retailers, so they do not reflect a retailer's pricing decisions, which is of primary interest here. In-store displays had the highest shares, and feature ads had comparably lower shares but were significant.

Finally, out of 96 stores available in the dataset, only 67 are considered in the analysis, because of the missing store traffic data problem. The excluded stores were those with more than 1 percent of missing customer traffic data – stores with more than

10 (out of 924) days missing. Some stores have not reported their customer count although their activity is present in movement files.

Table 3.2. Basic Characteristics of Raw Data

Category	**Number of UPCs**	**Promotion Type as a Share of Total Number of Observations**			**Total Number of Observations**
		Feature ad (S)	**Display (B)**	**Coupon (C)**	
Analgesics	461	0.37	1.68	0.02	1,852,537
Bath Soap	256	0.43	3.11	0.00	289,698
Beer	439	0.26	12.07	0.02	1,514,735
Bottled Juices	297	1.88	14.60	0.05	1,669,809
Cereals	322	0.92	4.71	0.05	1,909,910
Cheeses	444	1.23	14.41	0.19	2,570,032
Cigarettes	367	0.00	0.00	0.00	1,430,911
Cookies	765	0.87	8.46	0.03	3,751,861
Crackers	217	0.99	13.26	0.01	942,320
Canned Soup	350	1.98	8.98	0.01	2,091,497
Dish Detergent	208	0.83	7.40	0.00	1,040,420
Front-end Candies	373	0.28	5.35	0.06	1,875,819
Frozen Dinners	160	3.84	13.02	0.00	624,844
Frozen Entrees	557	3.27	7.21	0.00	3,064,983
Frozen Juices	124	3.22	12.21	0.00	792,066
Fabric Softeners	208	0.76	7.69	0.01	1,106,096
Grooming Products	719	0.52	3.96	0.01	2,698,118
Laundry Detergents	409	1.15	8.12	0.01	1,813,550
Oatmeal	76	0.50	8.03	0.00	478,874
Paper Towels	104	1.64	12.78	0.04	534,488
Refrigerated Juices	138	2.39	17.87	0.03	758,173
Soft Drinks	948	10.69	8.94	0.40	4,114,617
Shampoos	1,863	0.82	3.95	0.01	5,128,824
Snack Crackers	280	1.93	14.09	0.05	1,462,604
Soaps	182	0.68	10.15	0.00	911,426
Toothbrushes	372	1.40	3.68	0.02	1,191,812
Canned Tuna	195	0.32	12.83	0.00	1,106,124
Toothpastes	392	1.48	3.62	0.00	1,588,337
Bathroom Tissues	76	3.15	19.00	0.05	420,976

* Total number of observations is obtained as a simple count of all UPCs in all 67 stores available during a two and a half year long period (132 weeks).

One of the typical features of the supermarket price data is a characteristic price movement. As Figure 3.1 shows, there are several typical levels, which are interchangeably “visited” by the retail price. In the above graph, the price of $12.5 corresponds to a modal or pre-advertised price, and all temporary departures from it end up as a return to the stable higher price. Promotional periods usually last for two weeks, but sometimes extend to four or even six weeks.

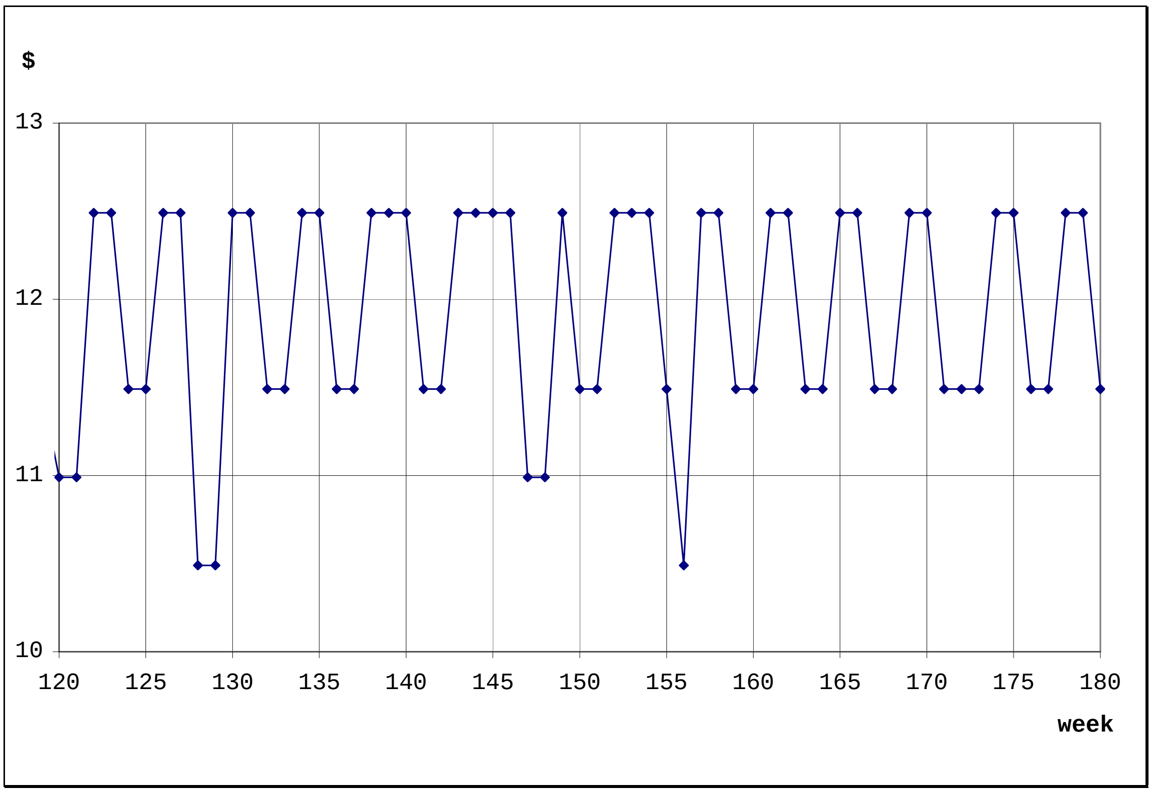

Figure 3.1. Retail Price Movement of Miller 24-pack 12 oz Beer

3.2. Variables

Since the main topic of the research is the promotional activity vis-à-vis store traffic, some rigor had to be exercised in defining promotions in a temporal sense. Sales are temporary price reductions followed by similarly sized price increases. There are instances in the data of "sale" periods lasting for 15 or even 20 weeks, but these cannot be seen as temporary. The only considered periods of promotion are those lasting from 1 to 6 weeks.

Raw data does not contain advertising expenditures, or any monetary form of promotional activity. These had to be obtained, i.e. approximated from the information already available. The point of interest was the volume of promotional activity by a store, and this will be named "total promotional discounts." For the purpose of approximating total promotional discounts, a "pre-advertising price" was constructed. This is the price of an item prior to the promotional period. The total promotional discounts are obtained as a product of the difference between pre-advertising and advertised prices on one side and the quantity sold on the other. On a few occasions total promotional discounts were negative (pre-advertising price lower than advertised price), but these were eliminated from the analysis. Also, some outliers of profit margins[5] were eliminated from the data.

Although it seems reasonably simple to pick the pre-advertising price, this was a challenging task and required quite a bit of complex programming to minimize prospects

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[5] A profit margin of 70 of a 10 dollar item corresponds to a wholesale price of $3. If the margin was -70, wholesale price of a 10 dollar item would be $17. All cases of a margin less than -70 and greater than 70 were eliminated. They were extremely rare. Actually, anything above 40 and below -40 was hardly ever seen. Considering how massive the dataset is, the effects of these eliminations are negligible.

for mistakes. Manual processing could not be used, and even manual corrections of the processed datasets are nearly impossible[6], due to the dimensions of the datasets. Separate programming was applied for traffic and promotional data, and they were later merged. Table 3.3 shows an excerpt from an already processed dataset. What was complex in selecting pre-advertising prices was the number of constraints that had to be fulfilled[7].

Table 3.3. Snapshot of a Partly Processed Dataset

STORE	UPC	WEEK	MOVE	QTY	PRICE	PRADV	SALE	PROFIT	OK
...	...	...	...	...	...			...	...
71	7199011600	149	3	1	11.99			1.16	1
71	7199011600	150	9	1	10.99	11.99	B	7.82	1
71	7199011600	151	2	1	10.99	11.99	B	7.82	1
71	7199011600	152	0	1	0			0	1
71	7199011600	153	1	1	11.99			1.16	1
71	7199011600	154	0	1	0			0	1
71	7199011600	155	1	1	11.99			1.16	1
71	7199011600	156	18	1	9.99	11.99	S	18.61	1
71	7199011600	157	5	1	10.99	11.99	B	7.82	1
71	7199011600	158	1	1	11.99			1.16	1
...	...	...	...	...	...			...	...
71	7199011600	198	3	1	11.99			1.16	1
71	7199011600	199	4	1	11.99			1.16	1
71	7199011600	200	80	1	8.99	11.99	S	-31.81	1
71	7199011600	201	27	1	9.99	11.99	S	-18.61	1
71	7199011600	202	2	1	11.99			1.16	1
71	7199011600	203	3	1	11.99			1.16	1

Using the newly constructed working variable "pradv", i.e. pre-advertising price, the promotional discounts (PROMDISC) were calculated for each sale occurrence, as

[6] In order to minimize the margin of error, an auxiliary file was constructed with all possible problems and complications, and computer code was pre-tested prior to being applied to the datasets.
[7] These include: renewing sequences of weeks, UPCs, stores, missing data, interrupted promotional periods, predefined sale periods, and many others.

equation (3.1) shows.

$$(3.1) \qquad PROMDISC_{ijut} = (p_{iju,t-k} - p_{ijut})q_{ijut}S_{ijut}\,,$$

where p_{ijut} is a price of an item with UPC code *u* that belongs to category *j* at store *i* in week *t*; $p_{iju,t-k}$ is a pre-advertising price of an item with UPC code *u* that belongs to category *j* at store *i* in week *t* – *k*, where *k* is a length of sale period; q_{ijut} is a quantity sold of an item with UPC code *u* that belongs to category *j* at store *i* in week *t*; and S_{ijut} is an index equal to one if an item with UPC code *u* that belongs to category *j* at store *i* in week *t* was on sale (feature ad or in-store display).

In order to handle this immense dataset, the analysis calls for aggregation with respect to UPCs within a category, as well as with respect to categories at a later stage[8]. The first two variables constructed are: (i) total promotional discounts ratio; and (ii) price decrease ratio.

Total promotional discounts ratio (PROMRAT) is given in equation (3.2):

$$(3.2) \qquad PROMRAT_{ijkt} = \frac{\sum_{u=1}^{U}\sum_{k\subseteq K}\left(p_{iju,t-k} - p_{ijut}\right)q_{ijut}S_{ijut}}{\sum_{u=1}^{U} p_{ijut}\, q_{ijut}} \cdot 100\,.$$

The numerator includes all sales of category *j* that belong to a set of up to *k* weeks long sale periods[9] in week *t* at store *i*. The denominator represents the current week’s category revenue. This ratio shows the relative size of category-related promotional activities compared to its revenues.

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[8] The advantages of aggregation were discussed in Chevalier, Kashyap, and Rossi (2003, p. 25).

[9] For 1 UPC, 1 week, and 1 store there could not be multiple promotional volumes in “*k*” sense – if an item is on sale in week *t* it can belong to 1, 2 week or a longer sale period, but not more than one of them in that week.

Table 3.4 provides information about the relative size of the categories' promotional activities compared to the weekly revenues they generated. Although any ratio above 100 could look suspect, such observations are normal. For example, frozen juices had a maximum promotional discounts ratio for an up to two-week long sale period equal to 130.10 at store 74 in week 188. This number means that promotional discounts exceeded current weekly revenue generated by frozen juices. Obviously, there are only three (out of six) definitions of the sale, which are presented here – up to two weeks long sale periods, then four and six, respectively.

Looking at the mean values of total promotional discounts ratio, the most heavily promoted is the soft drinks category. Depending on the accepted definition of sale, a value between 15 and 17 percent of revenues generated by soft drinks is directed towards promotion. Frozen entrees, frozen juices, and refrigerated juices have about ten percent of their revenues' worth in promotions. Although the other categories do not experience such high values of promotional discounts, even 3 to 5 percent represents a considerable amount of money.

The promotional frequencies should help better describe some of the patterns in the data. Table 3.5 shows how frequently each of the categories was promoted, as well as the importance of the two promotional types. To some extent there is a contrast to Table 3.4: some of the categories whose relative size of promotional discounts was not too large are actually promoted on a regular basis. For example, snack crackers had quite a modest promotional discounts ratio, but this category is promoted very frequently. On the other hand, soft drinks have the highest values of total promotional discounts ratio, and they are promoted very frequently, too. Nearly 20 percent of all selling activity had some sort of promotion involved. Feature ads promotions win over in-store displays only for the soft drinks category. Beer is almost exclusively promoted via in-store displays.

Table 3.4. Total Promotional Discounts Ratio Descriptives

Category	Sale Period Lasts								
	Up to Two weeks			Up to Four Weeks			Up to Six Weeks		
	Mean	Median	Max	Mean	Median	Max	Mean	Median	Max
Analgesics	1.27	0.55	38.39	1.32	0.57	38.39	1.32	0.57	38.39
Bath Soap	1.81	0.52	45.99	2.22	1.02	45.99	2.29	1.11	45.99
Beer	4.92	4.57	22.08	6.11	5.85	22.08	6.22	5.97	22.08
Bottled Juices	2.58	0.98	47.77	3.78	2.03	47.77	4.26	2.53	49.79
Cereals	2.26	0.72	33.78	2.53	0.95	33.81	2.57	0.98	33.81
Cheeses	2.15	1.28	48.97	3.43	2.31	49.55	3.82	2.69	50.39
Cookies	4.27	0.82	144.04	5.94	2.36	144.55	6.14	2.61	144.55
Crackers	2.59	0.27	64.75	4.42	1.58	67.24	4.75	1.80	67.99
Canned Soup	1.97	0.39	36.57	2.36	0.72	38.01	2.47	0.84	43.40
Dish Detergent	2.68	0.92	70.18	3.34	1.50	70.27	3.52	1.70	70.27
Front-end Candies	1.42	0.00	55.71	1.76	0.14	55.71	1.98	0.29	59.72
Frozen Dinners	6.82	1.56	92.46	8.26	3.22	92.46	8.56	3.39	92.46
Frozen Entrees	10.09	2.91	100.09	10.82	3.81	100.19	10.88	3.89	100.19
Frozen Juices	8.10	4.72	130.10	9.93	6.47	131.23	10.11	6.71	131.32
Fabric Softeners	1.89	0.80	29.02	2.40	1.35	34.29	2.61	1.51	34.29
Grooming Products	1.23	0.84	17.03	1.37	0.96	17.03	1.39	0.97	17.03
Laundry Detergents	5.00	2.57	87.36	5.81	3.49	87.80	6.06	3.72	87.80
Oatmeal	1.28	0.00	52.44	1.58	0.15	58.96	1.87	0.27	89.76
Paper Towels	2.19	0.64	58.54	3.02	1.25	59.65	3.71	2.10	59.65
Refrigerated Juices	7.09	3.24	101.21	9.75	6.29	101.97	11.16	7.78	101.97
Soft Drinks	14.86	13.85	65.66	16.53	15.87	65.66	17.33	16.77	65.66
Shampoos	2.34	1.72	23.06	2.62	2.05	26.89	2.65	2.07	26.89
Snack Crackers	1.56	0.53	60.28	3.15	1.60	60.31	4.35	2.11	60.32
Soaps	1.31	0.45	30.27	1.83	0.96	30.63	2.55	1.59	30.77
Toothbrushes	2.85	1.59	30.49	3.37	2.05	30.49	3.42	2.12	30.49
Canned Tuna	2.46	0.40	93.93	3.21	1.22	93.95	3.71	1.63	94.01
Toothpastes	2.96	1.82	44.30	3.37	2.21	44.30	3.39	2.24	44.30
Bathroom Tissues	5.69	2.11	101.40	6.40	3.00	101.40	7.05	3.78	101.40

Table 3.5. Percent Frequencies of Promotions

Category	Promotional Type as Percent of Valid Observations*			Promotional Type as Percent of Valid Promotions**		
	All	Display	Feature	All	Display	Feature
Analgesics	2.07	1.69	0.38	100.00	81.51	18.49
Bath Soap	3.57	3.14	0.43	100.00	88.10	11.90
Beer	12.42	12.17	0.26	100.00	97.91	2.09
Bottled Juices	16.64	14.74	1.89	100.00	87.66	12.34
Cereals	5.68	4.75	0.93	100.00	83.38	16.62
Cheeses	15.80	14.56	1.24	100.00	91.81	8.19
Cookies	9.42	8.54	0.88	100.00	89.76	10.24
Crackers	14.38	13.39	1.00	100.00	91.09	8.91
Canned Soup	11.08	9.07	2.01	100.00	81.31	18.69
Dish Detergent	8.30	7.47	0.84	100.00	88.58	11.42
Front-end Candies	5.67	5.39	0.28	100.00	94.31	5.69
Frozen Dinners	17.08	13.19	3.89	100.00	75.25	24.75
Frozen Entrees	10.58	7.27	3.31	100.00	65.03	34.97
Frozen Juices	15.58	12.33	3.25	100.00	77.51	22.49
Fabric Softeners	8.54	7.77	0.77	100.00	89.03	10.97
Grooming Products	4.53	4.00	0.53	100.00	87.40	12.60
Laundry Detergents	9.37	8.20	1.16	100.00	85.29	14.71
Oatmeal	8.60	8.09	0.51	100.00	93.26	6.74
Paper Towels	14.55	12.90	1.65	100.00	86.34	13.66
Refrigerated Juices	20.45	18.04	2.41	100.00	87.49	12.51
Soft Drinks	19.84	9.04	10.81	100.00	38.06	61.94
Shampoos	4.82	3.99	0.83	100.00	82.04	17.96
Snack Crackers	16.17	14.22	1.96	100.00	86.54	13.46
Soaps	10.93	10.25	0.68	100.00	92.59	7.41
Toothbrushes	5.13	3.72	1.42	100.00	70.66	29.34
Canned Tuna	13.28	12.96	0.32	100.00	97.11	2.89
Toothpastes	5.16	3.67	1.49	100.00	70.79	29.21
Bathroom Tissues	22.39	19.22	3.17	100.00	83.07	16.93

* Valid observations are those with flag ‘OK’ equal 1.
** Valid promotions are 1 to 6 weeks long.

Feature ads serve the purpose of attracting customers into stores. This type of promotion is usually associated with loss leaders. Out of the categories observed in this dataset, frozen dinners, frozen entrees, soft drinks are thus potentially loss leaders. In order to be absolutely certain that an item is promoted as a loss leader, at least two major conditions need to be satisfied: (i) it should be promoted as a feature ad (outside of the store); (ii) it should be sold at a loss, or near zero marginal profit. The former condition is easily verified. It is the latter condition that cannot be verified due to the nature of wholesale prices available. As mentioned earlier, these are the average acquisition costs, and not replacement costs.

Table 3.6. Percent Frequencies of Promotions' Duration

Category	**Length of Sale Period (Weeks)**						**Valid Promotions**
	1	**2**	**3**	**4**	**5**	**6**	
Analgesics	44.65	45.42	8.39	0.99	0.17	0.37	100.00
Bath Soap	37.97	33.86	15.99	7.92	3.39	0.87	100.00
Beer	17.39	66.77	10.83	3.13	1.18	0.71	100.00
Bottled Juices	21.43	25.57	22.51	14.87	10.89	4.73	100.00
Cereals	42.32	27.71	15.44	8.82	3.24	2.47	100.00
Cheeses	18.82	25.73	23.66	18.08	8.90	4.81	100.00
Cookies	17.18	21.02	29.12	23.70	6.47	2.51	100.00
Crackers	15.30	26.07	27.42	20.85	5.62	4.74	100.00
Canned Soup	30.95	22.04	20.49	13.76	8.06	4.69	100.00
Dish Detergent	23.78	29.13	16.90	12.87	10.16	7.16	100.00
Front-end Candies	20.38	26.45	21.03	14.90	14.53	2.71	100.00
Frozen Dinners	35.07	31.99	17.26	8.62	5.04	2.02	100.00
Frozen Entrees	46.21	29.40	14.71	6.39	2.42	0.87	100.00
Frozen Juices	32.16	32.26	21.93	7.69	4.70	1.27	100.00
Fabric Softeners	22.25	25.77	19.61	14.38	10.72	7.27	100.00
Grooming Products	42.80	42.88	7.96	4.52	1.34	0.49	100.00
Laundry Detergents	24.13	29.19	15.89	13.65	9.95	7.19	100.00
Oatmeal	21.77	30.26	23.72	8.22	9.99	6.04	100.00
Paper Towels	24.58	22.69	15.76	14.51	12.32	10.14	100.00
Refrigerated Juices	22.98	27.28	24.49	14.27	5.29	5.70	100.00
Soft Drinks	53.32	23.65	10.04	5.50	5.20	2.29	100.00
Shampoos	47.70	38.98	7.00	4.68	1.11	0.53	100.00
Snack Crackers	15.96	22.11	22.88	21.73	10.83	6.50	100.00
Soaps	16.34	23.79	15.56	13.15	17.57	13.60	100.00
Toothbrushes	53.50	30.92	8.46	6.01	0.73	0.39	100.00
Canned Tuna	18.80	26.33	22.64	15.91	10.27	6.05	100.00
Toothpastes	51.31	35.58	8.05	4.33	0.47	0.26	100.00
Bathroom Tissues	24.97	24.50	17.00	10.63	14.15	8.74	100.00

After looking at the relative importance of promotional discounts, as well as promotional frequencies, it would be useful to know the distribution of promotions' duration. The frequencies of different durations of sales could shed some light as to how categories differ in that respect.

Table 3.6 provides an overview of the frequencies of different duration of promotions for each category. Beer promotions typically last for two weeks (66.77 percent of all promotions). Crackers and cookies are sold on promotions lasting from one to four weeks. Overall, up to four week long sales are typical, but some extend to six weeks, as soap or paper towel categories do.

Another variable that has been constructed – price decrease ratio (PDRAT) – is given in equation (3.3):

$$(3.3) \qquad PDRAT_{ijkt} = \frac{\sum_{u=1}^{U} \sum_{k \subseteq K} \left(p_{iju,t-k} - p_{ijut} \right) q_{ijut} S_{ijut}}{\sum_{u=1}^{U} \sum_{k \subseteq K} p_{iju,t-k} \, q_{ijut}} \cdot 100 \, .$$

The numerator is exactly the same as that of equation (3.2), but the denominator is considerably different. It includes all sales of category *j* that belong to a set of up to *k* weeks long sale periods in week *t* at store *i*. This ratio is a weighted average of price cuts from the pre-sale price levels, over all UPCs within category *j* in a particular week at a particular store.

The descriptives by category are provided in Table 3.7. For short sale periods of up to two weeks long, the average price decrease ratio has a range of values from around 3 percent (oat meal) to nearly 21 percent (soft drinks). As the column of maximum values shows, prices decreased by 60, or nearly 70 percent, but these took place very rarely. In addition, several categories exhibit respective means high above the medians. These are cereals, cookies, front-end candies, frozen dinners, and refrigerated juices.

Table 3.7. Price Decrease Ratio Descriptives

Category	Sale Period Lasts								
	Up to Two weeks			Up to Four Weeks			Up to Six Weeks		
	Mean	Median	Max	Mean	Median	Max	Mean	Median	Max
Analgesics	13.48	10.31	60.32	14.02	10.96	60.32	14.04	10.98	60.32
Bath Soap	9.50	6.33	51.00	11.84	9.75	51.00	12.35	10.97	51.00
Beer	10.83	11.22	29.57	13.11	13.27	29.57	13.33	13.44	29.57
Bottled Juices	6.13	3.41	46.10	9.00	6.77	46.65	10.28	8.27	46.77
Cereals	10.07	5.87	66.13	11.56	7.37	66.20	11.77	7.57	66.20
Cheeses	6.28	4.57	47.15	10.14	8.83	49.21	11.42	10.04	49.34
Cookies	8.73	3.90	67.70	14.14	10.68	67.88	14.98	11.68	67.89
Crackers	5.37	1.39	50.84	10.23	6.52	52.88	11.24	7.44	52.88
Canned Soup	6.88	2.80	54.73	8.49	4.88	54.85	8.93	5.46	54.96
Dish Detergent	6.96	4.38	51.34	9.05	6.79	51.34	9.79	7.67	51.39
Front-end Candies	5.31	0.00	66.71	7.53	2.77	68.27	8.75	4.61	68.27
Frozen Dinners	11.36	6.02	66.47	14.30	11.48	66.55	15.08	11.91	66.55
Frozen Entrees	17.00	14.53	53.80	19.28	18.05	55.44	19.54	18.44	55.44
Frozen Juices	14.36	12.75	66.35	17.32	16.31	66.55	17.74	16.82	66.59
Fabric Softeners	5.92	3.98	45.03	7.58	5.91	45.19	8.39	6.89	45.19
Grooming Products	10.00	9.32	46.64	10.98	10.24	46.64	11.12	10.37	46.64
Laundry Detergents	9.82	7.69	57.66	11.84	10.28	57.95	12.44	10.92	57.95
Oatmeal	3.61	0.02	54.57	4.97	1.57	54.57	6.11	3.02	54.57
Paper Towels	4.45	1.90	48.18	6.05	3.70	49.07	7.63	5.91	49.16
Refrigerated Juices	10.46	6.77	53.26	14.70	11.93	54.71	16.90	14.70	54.72
Soft Drinks	20.81	21.04	51.91	23.21	23.68	58.02	24.34	25.41	60.90
Shampoos	14.38	13.26	42.64	16.29	15.63	52.15	16.49	15.88	52.22
Snack Crackers	4.19	1.75	47.93	7.85	5.79	47.96	10.08	7.94	47.97
Soaps	4.15	2.08	43.75	5.95	4.35	44.26	8.25	6.80	48.37
Toothbrushes	14.77	14.05	66.91	17.20	17.51	66.91	17.46	17.79	66.91
Canned Tuna	4.54	1.58	56.32	6.79	4.58	56.49	8.03	5.76	56.51
Toothpastes	12.16	10.91	68.45	14.14	12.57	68.45	14.36	12.81	68.45
Bathroom Tissues	8.50	5.64	52.90	10.04	7.76	52.90	11.18	8.79	52.90

Increasing the number of sale periods included in the definition of sale tends to increase the mean price decrease ratio values. For four week long sales, the average price decrease ratio is very high, about 23 percent for soft drinks. The most aggressively promoted categories are: frozen entrees, frozen juices, soft drinks, shampoos, and toothbrushes. Several categories experience very close values of their respective means and medians. These include soft drinks, beer, shampoos, toothbrushes and grooming products.

The descriptives given in Table 3.7 provide limited information on the distribution of price decreases. Clearly, there are categories whose measures of central tendency happen to be far apart. Although some of the categories have nearly identical values, a more detailed information about price decrease ratio frequencies would be useful. This is presented in Table 3.8.

After examining the frequencies provided in Table 3.8, it becomes clearer why some categories had median values significantly below their respective means. These have around one half of all price decreases in range between zero and five percent. Some categories frequently have very big price decreases. Price decreases above 30 percent are common for frozen entrees, soft drinks and shampoos, for example.

Table 3.8. Price Decrease Ratio Percent Frequency Distribution

Category	Price Decrease Ratio						
	0-5%	5-10%	10-15%	15-20%	20-25%	25-30%	>30%
Analgesics	34.89	19.98	13.01	9.76	8.88	4.69	8.78
Bath Soap	20.18	27.23	21.61	13.42	5.65	4.35	7.57
Beer	12.39	16.52	11.82	30.95	20.77	6.34	1.21
Bottled Juices	47.98	19.11	13.29	6.62	6.31	3.38	3.30
Cereals	51.06	15.61	10.03	5.16	2.96	9.62	5.56
Cheeses	49.24	17.82	9.08	5.98	6.24	9.37	2.26
Cookies	33.14	27.73	12.29	9.98	5.85	4.93	6.08
Crackers	44.65	27.16	10.67	4.88	3.48	3.33	5.83
Canned Soup	53.88	18.31	8.88	5.22	6.40	3.78	3.53
Dish Detergent	50.70	20.96	13.21	5.57	4.43	2.68	2.46
Front-end Candies	42.26	19.66	14.03	5.04	3.82	4.90	10.28
Frozen Dinners	35.26	14.11	13.04	8.47	7.72	8.86	12.54
Frozen Entrees	31.88	10.02	8.14	6.99	5.46	7.97	29.54
Frozen Juices	36.80	15.76	12.59	10.83	7.81	6.65	9.56
Fabric Softeners	53.03	19.52	11.79	6.74	4.11	2.52	2.28
Grooming Products	20.69	22.19	26.74	13.71	6.64	5.38	4.65
Laundry Detergents	46.08	18.79	12.79	7.80	6.03	4.19	4.32
Oatmeal	67.89	14.86	5.65	3.05	1.83	2.84	3.88
Paper Towels	45.08	23.42	13.48	7.74	4.48	3.84	1.96
Refrigerated Juices	40.87	16.76	12.77	8.51	6.70	6.26	8.13
Soft Drinks	15.16	10.79	15.97	10.34	12.50	10.62	24.62
Shampoos	16.45	16.30	16.19	9.12	14.02	8.90	19.03
Snack Crackers	37.69	24.35	13.99	6.55	4.61	5.15	7.66
Soaps	46.12	25.48	12.23	9.02	3.77	1.21	2.17
Toothbrushes	15.58	9.83	13.07	9.74	20.66	18.81	12.31
Canned Tuna	52.60	27.31	10.33	4.16	2.02	1.45	2.13
Toothpastes	22.05	21.09	17.84	15.46	11.24	5.60	6.71
Bathroom Tissues	44.60	22.11	10.96	8.85	5.35	3.61	4.52

At another, the highest, level of aggregation, the two variables would be defined for all twenty eight categories. Aggregated promotional discounts ratio (PROMRATA) is of the form:

$$(3.4) \qquad PROMRATA_{ikt} = \frac{\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{k\subseteq K}\left(p_{iju,t-k} - p_{ijut}\right) q_{ijut} S_{ijut}}{\sum_{j=1}^{J}\sum_{u=1}^{U} p_{ijut}\, q_{ijut}} \cdot 100,$$

where sales of all categories that belong to a set of up to *k* weeks long sale periods in week *t* at store *i* are included. This is a relative size of total promotional discounts compared to the store revenue created by these categories. Descriptives are given in Table 3.9.

Table 3.9. Aggregated Promotional Discounts Ratio Descriptives

Sales Last	Mean	Median	St. Dev.	Min	Max
1 week	4.29	3.47	3.49	0.00	30.15
up to 2 weeks	6.23	5.43	3.71	0.00	31.68
up to 3 weeks	7.00	6.20	3.85	0.00	32.92
up to 4 weeks	7.40	6.55	3.93	0.00	33.37
up to 5 weeks	7.71	6.84	3.99	0.00	34.00
up to 6 weeks	7.85	7.00	4.01	0.00	35.28

The most frequent length of sale period recorded (three or four weeks) brings about 7 percent of revenues generated to be devoted to promotional activity. As can be easily verified in equation (3.4), given values are averaged over all the stores, all weeks, and all the categories. This overview is informative, but there is still room for an improved image of the data behavior. Ascertaining the lower median value for any definition of sale used requires a more detailed look into total promotional discounts distribution. Table 3.10 provides percentiles overview of total promotional discounts at the highest level of aggregation.

Table 3.10. Aggregated Promotional Discounts Ratio Distribution

Sales last	**Percentiles**						
	5	**10**	**25**	**50**	**75**	**90**	**95**
1 week	0.31	0.93	1.96	3.47	5.54	8.69	11.31
up to 2 weeks	1.84	2.49	3.68	5.43	7.82	11.11	13.38
up to 3 weeks	2.29	3.09	4.37	6.20	8.75	12.06	14.35
up to 4 weeks	2.56	3.38	4.72	6.55	9.28	12.57	15.04
up to 5 weeks	2.72	3.56	4.96	6.84	9.69	13.02	15.44
up to 6 weeks	2.80	3.67	5.08	7.00	9.90	13.19	15.51

The price decrease ratio at the highest level of aggregation (PDRATA) provides an insight into how deep the price cuts are on average for twenty eight categories. These averages are calculated on a weekly basis. The following equation shows how it is constructed.

$$(3.5) \qquad PDRATA_{ikt} = \frac{\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{k\subseteq K}\left(p_{iju,t-k} - p_{ijut}\right) q_{ijut} S_{ijut}}{\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{k\subseteq K} p_{iju,t-k}\, q_{ijut}} \cdot 100 .$$

This ratio represents a measure of stores’ promotional activity. The calculated values are based on the weighted averages, and each store has a different value of this ratio for every week considered. The mean value of this aggregated version of price decrease ratio is between 10 and 18 percent. These are overall price cuts in all the stores, all the weeks, and all the categories considered. Table 3.11 contains descriptives for different definitions of sale.

Table 3.11. Aggregated Price Decrease Ratio Descriptives

Sales Last	Mean	Median	St. Dev.	Min	Max
1 week	10.05	9.25	6.14	0.00	34.10
up to 2 weeks	14.77	14.22	5.82	0.00	36.15
up to 3 weeks	16.68	16.23	5.77	0.00	38.37
up to 4 weeks	17.68	17.09	5.79	0.00	39.99
up to 5 weeks	18.42	17.88	5.78	0.00	40.17
up to 6 weeks	18.79	18.22	5.78	0.00	40.23

Another way to look at the aggregated price decrease ratio is to examine the distribution of price decreases. Table 3.12 presents a detailed view. The average price decrease ratio hardly reaches 30 percent even at the ninetieth percentile. Very big price decreases are rare. Nevertheless, it is useful to know that promotional price decreases tend to hover around the 15 to 20 percent mark.

Table 3.12. Aggregated Price Decrease Ratio Distribution

Sales last	Percentiles						
	5	10	25	50	75	90	95
1 week	0.93	2.95	5.69	9.25	13.31	18.28	22.36
up to 2 weeks	6.54	7.95	10.58	14.22	18.15	22.52	26.13
up to 3 weeks	8.43	9.91	12.69	16.23	19.93	24.57	27.75
up to 4 weeks	9.28	10.85	13.78	17.09	20.89	25.78	28.82
up to 5 weeks	9.87	11.57	14.55	17.88	21.81	26.62	29.12
up to 6 weeks	10.22	11.92	14.91	18.22	22.18	26.96	29.49

Different categories behave differently, and any kind of pattern or relationship between different measures could be of use. Table 3.13 provides an overview of all the measures given. There is evidence in the literature that frequent promotions are related to shallow price decreases. All significantly frequent promotions are related to low price decreases, but beer and soft drinks do not comply. These results would not hold if the average price decrease was used instead of typical price decrease ranges. In this case beer, frozen foods, refrigerated juice and soft drinks have significant mean price decreases corresponding to frequent promotions. Their mean values are driven by very high price decreases promoted occasionally, or the price decrease ranges through 20 or 25 percent with similar importance as the first two typical ranges of price decreases depicted in Table 3.13.

Also, significant promotional discounts, at least in terms of their relative size to the revenues generated, are short lived. Almost all of them have typical sale period of 1 to 2 weeks, which would suggest very aggressive and short periods of promotional activity. The only exception are cookies, which coincidentally have the lowest storage costs.

The last variable that needs to be introduced is the customer count or customer traffic (TRAFFIC). The dataset's usability is considerably constrained by the availability of traffic data. Since the first 93 weeks, as well as weeks 225 through 400 exhibit a very serious missing data problem, the only part of data used are weeks 94 through 225. Another constraint taken into consideration was the lack of data for some stores. Some of them had more than 60 percent of traffic data missing, although they had recorded activity in other parts of the dataset, namely in movement files. Consequently, only 67 out of 96 stores are included.

Table 3.13. General Overview of Categories' Characteristics

Category	**Promotional Discounts Ratio** (>5%)	**Promotional Frequency** (>10%)	**Price Decrease Ratio**			**Typical Length of Sale (weeks)**	
			Significant (mean>10%)	First (%)	Second (%)	First	Second
Analgesics			X	0-5	5-10	2	1
Bath Soap				5-10	10-15	1	2
Beer	X	X	X	15-20	20-25	2	1
Bottled Juices		X		0-5	5-10	2	3
Cereals			X	0-5	5-10	1	2
Cheeses		X		0-5	5-10	2	3
Cookies	X			0-5	5-10	3	4
Crackers		X		0-5	5-10	3	2
Canned Soup		X		0-5	5-10	1	2
Dish Detergent				0-5	5-10	2	1
Front-end Candies				0-5	5-10	2	3
Frozen Dinners	X	X	X	0-5	5-10	1	2
Frozen Entrees	X	X	X	0-5	5-10	1	2
Frozen Juices	X	X	X	0-5	5-10	2	1
Fabric Softeners				0-5	5-10	2	1
Grooming Products			X	10-15	5-10	2	1
Laundry Detergents	X			0-5	5-10	2	1
Oatmeal				0-5	5-10	2	3
Paper Towels		X		0-5	5-10	1	2
Refrigerated Juices	X	X	X	0-5	5-10	2	3
Soft Drinks	X	X	X	10-15	0-5	1	2
Shampoos			X	0-5	5-10	1	2
Snack Crackers		X		0-5	5-10	3	2
Soaps		X		0-5	5-10	2	5
Toothbrushes			X	20-25	25-30	1	2
Canned Tuna		X		0-5	5-10	2	3
Toothpastes			X	0-5	5-10	1	2
Bathroom Tissues	X	X		0-5	5-10	1	2

Even for these included stores some of the traffic data was missing. The number of missing days ranges from 2 to 9, which is all well below 1 percent of the available data. Two types of corrections were tried. The first model comes from Chevalier, Kashyap and Rossi (2003). They use a sample mean correction method for sales. If the data reported for the week contained Wednesday-Sunday, but not Monday and Tuesday, the data were scaled up by the sample average ratio of full week traffic to Wednesday through Sunday traffic. The available data in adjacent years was used to form samples, and then this sample mean was used to correct for the missing traffic. Caution was exercised to choose samples that resemble the original week that was being corrected – e.g. week before Thanksgiving.

Since the first method showed great distortions and the corrected data looked like outliers, another method was applied. This was the partial mean correction method. In a week that had missing traffic data, the available days' traffic would be used to construct a partial mean, and then this mean was applied as a replacement for the missing days' traffic. This method inevitably brought some distortion, but when compared to the former, the series looked considerably better. Finally, comparing the corrected series using the second method with the raw data shows a difference of 0.5 percent in the means. Table 3.14 presents a more detailed insight into differences between the two series.

Table 3.14. Traffic Data Correction, Descriptives and Distribution

Traffic data	**Mean**	**Standard Deviation**	**Percentiles**						
			5	**10**	**25**	**50**	**75**	**90**	**95**
Raw	19,699.08	4,816.80	12646	13856	15715	19389	23341	26334	27897
Corrected	19,803.19	4,801.40	12838	13976	15777	19513	23452	26404	27968
Difference	104.11	-15.40	192	120	63	124	112	70	71
% Difference	0.53	-0.32	1.52	0.87	0.40	0.64	0.48	0.27	0.25

3.3. Dummy Variables

The data has the time-series cross-sectional (TSCS) form. There are 67 stores and 132 weeks. Both of these dimensions need additional control throughout the estimation process. Cross sectional dimension requires one set of dummy variables. Each of the 67 stores has a corresponding dummy variable that takes a value of one when it is represented within the dataset. Although static demographic data is available for each store, the store dummy variable would, by construction, pick all the effects, including these.

On the other hand, time dimension is more complex. Four different sets of dummy variables were constructed. The first set is made of holiday and special events dummies. These include: Presidents Day, Memorial Day, July 4^{th}, Labor Day, Halloween, Thanksgiving, Post Thanksgiving, Easter, and Christmas. The construction of these dummy variables closely follows work by Chevalier, Kashyap and Rossi (2003). Weeks in this dataset start on Thursdays and end on Wednesdays. If a holiday lands on Thursday, the variable is set to one for the two weeks prior to the holiday, but 0 for the week including the holiday. For holidays taking place on all other days, the dummy variable is set to one for the week before the holiday, and for the week including the holiday. The Christmas dummy variable stays one for New Year's week, because it is very difficult to separate the two. The post Thanksgiving variable has a value of one for the week following Thanksgiving. Other variables are self-explanatory.

Another set of dummy variables is weather related. Daily weather data for the Chicago area was obtained from the National Oceanic & Atmospheric Administration (NOAA). The available data[10] included daily minimum, maximum, average temperatures, departure from normal temperature, precipitation, and snowfall. Another useful piece of data[11] were the major storm events. These included tornadoes, thunderstorms, high winds and hail. Three separate variables were constructed: (i) Precipitation for a particular week is set to value one when at least one daily record indicated more than 0.5 inches of rain. (ii) Snow would be set to one if there was at least one day in a week with snowfall exceeding 2 inches. (iii) Storm would be set to one for any major storm event that happened in some week. There were 14 of them, including several tornadoes.

Finally, one joint dummy variable is constructed based on the above three, and it is called Bad Weather. This one includes all three and is set to one when either of the above three had value of one.

[10] NCDC Climate Data Online. National Oceanic & Atmospheric Administration (NOAA), the National Climatic Data Center website, <http://cdo.ncdc.noaa.gov/CDO/cdo> (Accessed on: July 26, 2005).
[11] NCDC Storm Event database, National Oceanic & Atmospheric Administration (NOAA), the National Climatic Data Center website, <http://www7.ncdc.noaa.gov/IPS> (Accessed on: July 26, 2005).

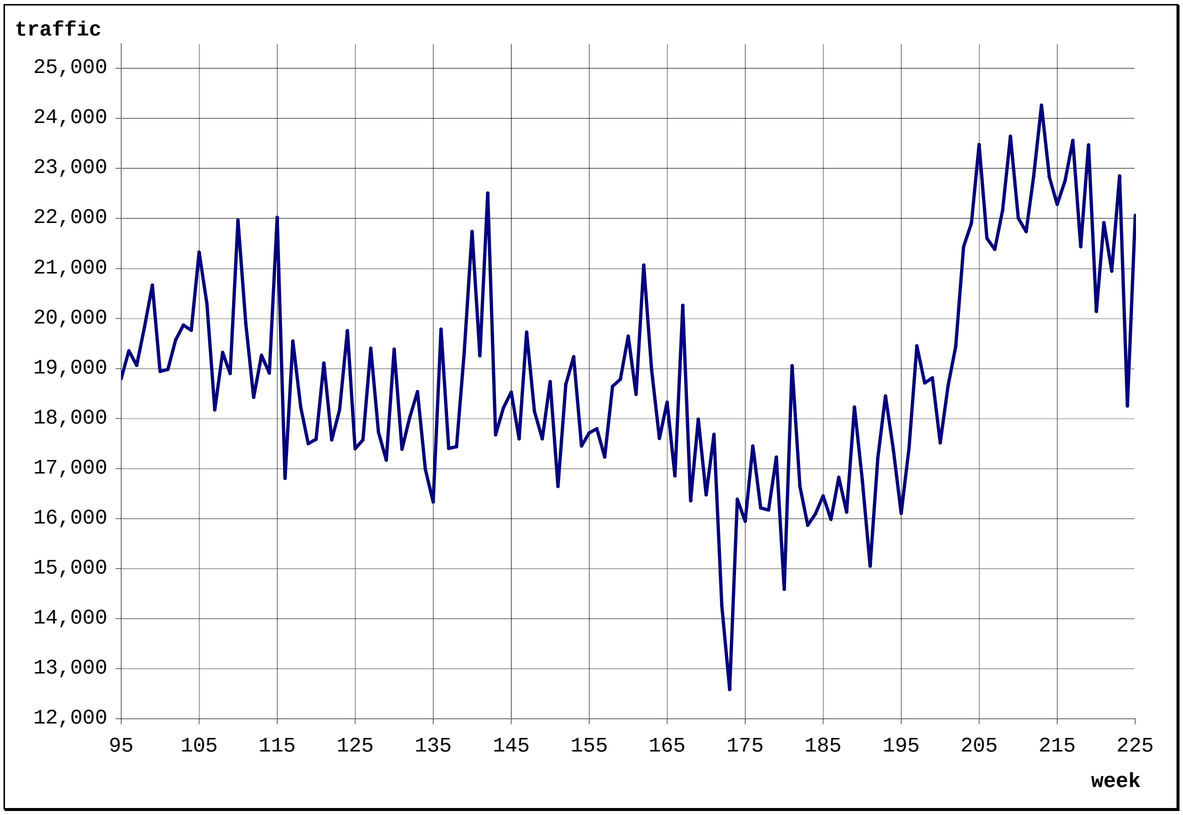

Figure 3.2. Traffic Data Graphical Break Detection – Store 68

The third group of dummy variables is constructed to identify the break points in the traffic data. Although it would be possible to use grid search methods to find those breaks, they can be detected from the figures. Some of these breaks are easily recognized because they represent very significant changes in weekly traffic data. A good example is store number 68. It's given in Figure 3.2, where traffic is a subject of a clear break in week 203.

There is an identifiable trend break for all 67 stores, visible in Figure 3.3. It seems to be attributable to Halloween week (164), but this is the week of the 1992 US

Presidential Elections. For many stores, the trend was flat or negative up to that point, but after week 164 it becomes positive, or considerably less negative. This break was identified using Chow's Breakpoint test. In case of one suspected break, two sub-periods are fit separately, and the test checks if there are systematic differences in the estimated equations. Null hypothesis of no trend break was rejected for all 67 stores[12].

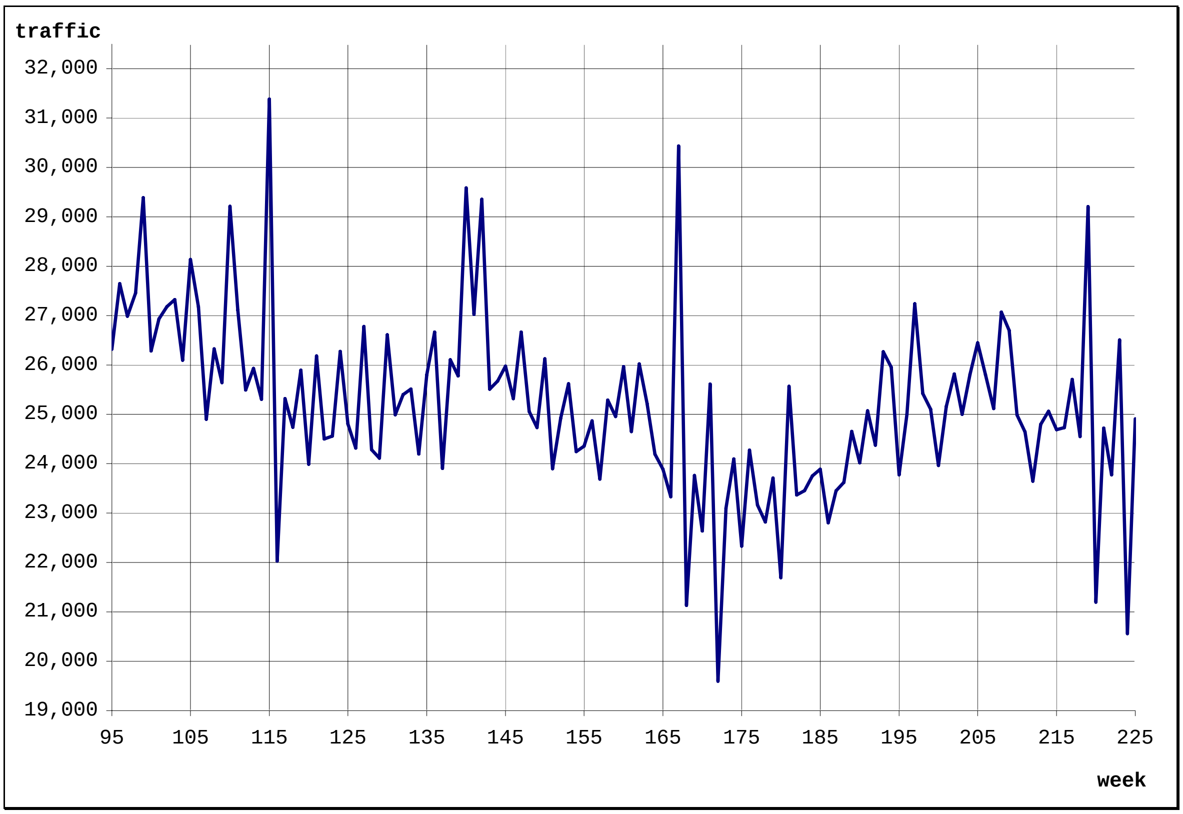

Figure 3.3. Traffic Data Trend Break Detection – Store 124

[12] Null hypothesis of no trend break was rejected for 57 stores at 1 percent significance level, but for 65 stores at 5 percent significance level.

Based on identified breaks, a full set of interactive trend-break variables was constructed. These are simple multiplications of trend and dummy break variables. Quadratic trend was also constructed, but would not show as significant in later analyses. Another form of time dimension controls was constructed as weekly dummy variables, but trend-break variables showed as being much better time dimension controls.

4. STATIC MODEL

The main interest of this dissertation is the relationship between store traffic and various measures of supermarket promotional activity. The data is of the time series cross section form, and it is unbalanced. Although panel data estimators are good candidates for the analysis, a closer look at the dimensions of this "panel" reveals a multiple time series nature: the cross section dimension is smaller than the time dimension[1]. This is an important feature of this data, because it directly determines the quality and applicability of various estimators.

An extensive search for model specification has been performed. Many characteristics of the supermarket industry had to be taken into account during the process. It is well established in the literature that demographic and locational characteristics of neighborhoods and the stores serving them play an important role in the supermarket industry. These have to be controlled for. Since the data contains only static demographic profiles of each store based on the 1990 US Census, it would be difficult to produce a dynamic profile without many assumptions and approximations[2]. Not too many changes in demographic profiles materialized during the two and a half year long period considered here[3]. The Chicago Metropolitan Area is somewhat specific because it has very well established neighborhoods and community areas, and these did not change much during the period under investigation.

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[1] There are 67 stores (N = 67) and 132 weeks (T = 132).
[2] It is possible to construct demographic profile for each store based on the 2000 US Census data, and then use interpolation. Various neighborhood types and their 1990 and 2000 characteristics are available on the web at http://www.lib.uchicago.edu/e/su/maps/
[3] Decennial US Census Online, U.S. Census Bureau, <http://factfinder.census.gov> (Accessed on: December 5, 2003).

Another important dimension to be considered is the competition environment in which Dominick's Finer Foods operated. Once again, the Chicago area is specific in that there is only one major supermarket chain competing with Dominick's – Jewel-Osco. Each of the 67 Dominick's stores included in the analysis faced a direct competition from at least one Jewel-Osco store. During the 132 week long period there was virtually no change in store composition[4]. Some major changes did occur[5] in 1994 and 1995, but that is well beyond the examined time frame.

Before any specification test was performed, the data was first checked for possible non-stationarity[6]. Unit-root tests on all series (customer traffic, promotional discounts ratio, price decrease ratio) were run, and there was no trace of unit-roots. Namely, Augmented Dickey-Fuller tests were run on 67 individual time series, and showed that MacKinnon critical values were above (less negative than) test statistics. Then Fisher's test for panel data[7] was run and also showed no unit root in any series examined. Another source of non-stationarity could be deterministic trend[8], but no trace

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[4] In other words, if Thiessen (Voronoi) polygons were defined, they would not change. Thiessen polygons are mathematically defined by the perpendicular bisectors of the lines between all points. Their boundaries define the area that is closest to each point relative to all other points.

[5] Yearly data on existence of several retail chains (Shop N Save, Treasure Island, White Hen Pantry, Whole Foods Market, Wal-Mart, Aldi, Convenient Food, Cub Foods, Dominicks Finer Foods, Eagle Food Center, Hy-Vee Food Stores, Jewel-Osco, JJ Peppers, KMart, Kroger, Meijer, Omni, Save-a-Lot, Seven Eleven) was collected from telephone directory microfiche files stored at the Chicago Public Library. Data for eight areas was collected: Chicago, Joliet, South, Northwest, Near West, Near North, Far North, and Far West.

[6] A typical case of two variables trending together over time may lead to conclusion that they are related, although they are not. Stationarity is important to avoid spurious regressions.

[7] Fisher's test combines p-values from 67 independent unit root tests. It assumes that all series are non-stationary under the null hypothesis against the alternative that at least one series in the panel is stationary. Chi squared values obtained are above 4400 for all three series examined (for 134 degrees of freedom).

[8] When trend is included in Augmented Dickey-Fuller tests or Fisher's test, obtained test statistics are above 4380 for all three series at 134 degrees of freedom. Since a trend break was detected, separate tests were run on subsets of observations (before and after the break), and very similar values of the test statistic are obtained. A detailed description of testing methodology could be found in Enders (1995, pp. 256-258).

of non-stationarity was found again.

Since it is established that regressing customer traffic on promotional activity measures is safe from a stationarity standpoint, the search for right specification could start. Both demographic and competitive dimensions remained unchanged throughout the analyzed period. These are directly related to stores, and they could be accounted for by the use of individual effect parameters. Usage of store specific dummy variables needs to be justified and therefore checked. The specification search could begin with an ordinary least squares model. It is always useful to check whether the poolability of this data could be considered as an option. The Breusch and Pagan Lagrangian multiplier test showed that individual effects are significant[9], and that poolability is not acceptable. Also F tests show that individual effects are significant, and that poolability can be rejected[10]. Demographic, locational, and competitive factors must be included in the model from the very beginning.

The dataset contains weekly measures of promotional activity (promotional discounts ratio and price decrease ratio), customer traffic, and a series of dummy variables covering weather, holidays, breaks in data, etc. Time dimension should be well represented in the model. There are two issues that pertain to temporal dimension: i) controlling for time aspects of data (trend, holidays, breaks); and ii) including a correct number of lagged values of the variables to capture potential dynamics.

[9] Obtained chi square values are $4 \cdot 10^5$ for both price discounts ratio and price decrease ratio.
[10] It is not possible to apply a simple Chow test which assumes homoskedastic panel variances. A generalized Chow test allows for heteroskedastic variances and it is used here. See Baltagi (2005, p. 55) for details. Obtained $F_{(66, 8489)}$ value is 1,192.49 for promotional discounts ratio, and 1,189.59 for price decrease ratio. The critical value for the respective degrees of freedom is 1.3042.

There are two possible ways to control for time. A separate time dummy variable for every week[11] could be included. If this method were used, measures of holiday effects would be lost among many dummy variables. These measures are of interest for at least two reasons: i) seasonal effect could be considerable and needs to be controlled for and recorded, and; ii) specification errors would be detected if signs of the effects are different from what was expected. Another method for time control is the inclusion of store-individual trends[12] combined with holiday and weather dummy variables. From an informative perspective it is more useful to know the effects of holidays and weather, as well as store-specific trends. Although both methods are tested, the latter provides more information.

All candidate specifications will be checked against the base model. If there are improvements in fit over the base model, it would be clear that such a 'candidate' model would be preferred. The Base model can be represented by equation (4.1)

$$y_{it} = \alpha + \nu_i + \beta x_{it} + \varepsilon_{it},\ i = 1,...,67;\ t = 1,...,132, \tag{4.1}$$

where y_{it} represents customer traffic, x_{it} is the measure of retailer's promotional activity (promotional discounts ratio or price decrease ratio), α is intercept, ν_i is store-specific unobserved effect, β is the coefficient to be estimated, and ε_{it} represents idiosyncratic error.

Starting from this Base model, four different measures will be taken and compared with those from other specifications. These include: the root mean squared

[11] This together with individual stores' dummies would create Two-Way Error Component Model.
[12] Breaks in these trends are accounted for by means of dummy variables.

error (RMSE)[13], the adjusted R-square[14], the Akaike Information Criterion (AIC), and the Schwarz Bayesian Information Criterion (SBC)[15].

Equation (4.1) could be estimated using fixed effects or random effects estimators. The choice between these two is not always simple, nor is there any simple test that could make such a decision for an analyst. The fixed effects estimator is used if a specific set of stores is observed (no random draw), and the inference is conditional on the stores observed. This model allows for the endogeneity of all the regressors with individual effects. The random effects estimator could be used if there is a random draw of stores from a large store "population." Individual effects would be characterized as random (exogenous with all the regressors), and inference pertains to the population from which this sample is randomly drawn.

Based on these assumptions, and given the characteristics of the dataset available, a fixed effects model would be preferred, but this needs to be formally checked. As previously mentioned, there is no test that could make this choice, but some tests can provide help during the process. Namely, the Hausman specification test, which

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[13] Root Mean Square Error (RMSE) is the standard deviation of the error term, and is the square root of the Mean Square Residual (or Error). A ratio of candidate model's RMSE to the base model's RMSE will be being reported.
[14] Unlike R square, adjusted R square allows for the degrees of freedom associated with the sums of the squares. Therefore, even though the residual sum of squares decreases or remains the same as new explanatory variables are added, the residual variance does not. For this reason, adjusted R square is generally considered to be a more accurate goodness-of-fit measure than R square.
[15] AIC = T ln(residual sum of squares) + 2n; SBC = T ln(residual sum of squares) + n ln(T), where n is the number of parameters estimated, T is the number of usable observations. Increasing the number of regressors increases n, but should have the effect of reducing the residual sum of squares. Thus, if a regressor has no explanatory power, adding it to the model will cause both AIC and SBC to increase. Since ln(T) will be greater than 2, the SBC will always select a more parsimonious model than the AIC; the marginal cost of adding regressors is greater with the SBC than the AIC. (Enders (1995, p. 88)) Both AIC and SBC penalize for the addition of parameters, and thus select a model that fits well but has a minimum number of parameters (i.e. simplicity and parsimony).

is based on the difference between fixed and random effects estimators. The null hypothesis reads that the difference in coefficients obtained by these two estimators is not systematic. Baltagi (2001, p. 20) explains that applied researchers unfortunately interpret rejection of the null as an adoption of the fixed effects model, and non-rejection as an adoption of the random effects model. As Hsiao (2003, p. 51) shows, this test should be used as an indication of misspecification in the random effects model.

Systematic difference in the coefficients from the two estimators may exist for two reasons: (i) there is a misspecification in the random effects model; or (ii) regressors are correlated with individual effects. After running both regressions (fixed and random effects) on equation (4.1), a null hypothesis of no difference between coefficients was accepted at 5 percent. Obtained chi square value is 2.51[16], and the critical value at 5 percent and at 1 degree of freedom is 3.84. The fixed effects model shows some correlation between individual effects and regressor (0.0562). Although this does not seem to be much[17], the fixed effects estimator is robust to such a correlation, and the other estimates it produces are unbiased.

Starting with the Base model given in equation (4.1), additional variables are added, and the measures of goodness-of-fit recorded and compared to those from the

[16] Vince Wiggins (StataCorp) provides code for the augmented regression based on Mark Schaffer's and Carl Nelson's artificial regression for Hausman-type-test. It nests both random and fixed effects models and allows performing a simple Wald test on a set of jointly estimated coefficients. This code overcomes several problems the official Stata's Hausman test module has (constant covariates within panels and missing data). In some cases Stata's module fails, and provides negative value of chi square test. Wiggins, V., "Re: st: hausman and xthausman after panel fe, re - DROPPED MEAN/DIFF," 26 Aug 2005, <http://www.stata.com/statalist/archive/2005-08/msg00853.html> (Accessed on: January 16, 2006).
[17] This Base model shows the smallest amount of correlation between regressors and individual effects. During the specification search this correlation becomes more pronounced, and differences in coefficients estimated by random and fixed effects models become significant. The augmented regression for Hausman test provided values of chi square well above 10,000, rejecting the null of no difference in coefficients.

base model. The estimator used for the specification search is the fixed effects model, as shown previously. One of the specifics of the reported R-square from the fixed effects model is the exclusion of the effects of the groups (individual dummies), before the fit is performed. They are subtracted from the model, since they are assumed to be fixed quantities, and their effect on the fit of the model is not quantified. If an ordinary least squares model is used, with individual stores' dummies added, the reported R-square will include the estimation of group effects before the fit is performed[18]. This is why R-square for the two estimators is very different. It is informative to have both of these estimators' R-squares reported.

The first alternative to the base model would have seasonal (holiday) dummies added. This model would be called 'Model 4.1', and is presented in equation (4.2):

$$y_{it} = \alpha + \nu_i + \beta x_{it} + \sum_{h \in H} \sigma_h s_h + \varepsilon_{it},\ i = 1,...,67;\ t = 1,...,132, \tag{4.2}$$

where s_h represents a holiday dummy variable, and σ_h are the coefficients to be estimated. A total of ten dummy variables is included[19]. Table 4.1 shows the comparison of 'Model 4.1' to the Base model.

The more important question is whether or not the inclusion of seasonal dummy variables helps achieve a better fit. The Root Mean Square Error (RMSE) obtained in Model 4.1 is lower than what has been obtained in the Base model. The RMSE Ratio of Model 4.1's RMSE to Base model's RMSE is short of 94 percent for both promotional variables considered. This is just a simple way of showing how the RMSE diminishes

[18] Total sum of squares is different for the fixed effects, and an OLS with dummy variables (Least Squares Dummy Variable Estimator). Residual sum of squares is the same.
[19] These are: President's Day, Memorial Day, July 4th, Labor Day, Halloween, Thanksgiving, Post-Thanksgiving, Easter, Christmas, and Non-Holiday (calm period between two holidays).

after the seasonal dummy variables are included. Both Akaike and Schwarz Bayesian Information Criteria show improved fit, because their values decrease. The R-square from the fixed effects model shows quite a big improvement in fit. This result was certainly expected, because seasonal effects can be large in the supermarket industry.

Table 4.1. Specification Search: Model 4.1

Measures of Goodness-of-Fit	**a) Promotional Discounts Ratio**				
	Base Model		**Model 1**		**RMSE Ratio (Model 1/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.02264	0.86463	0.13935	0.88079	
Adj. R-square	0.01492	0.86356	0.13153	0.87971	
RMSE	1,773.55	1,773.55	1,665.27	1,665.27	0.9389
AIC	17.79	17.81	17.67	17.68	
BSC	17.79	17.86	17.68	17.75	
Measures of Goodness-of-Fit	**b) Price Decrease Ratio**				
	Base Model		**Model 1**		**RMSE Ratio (Model 1/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.01263	0.86324	0.13560	0.88027	
Adj. R-square	0.00483	0.86216	0.12775	0.87919	
RMSE	1,782.61	1,782.61	1,668.89	1,668.89	0.9362
AIC	17.80	17.82	17.67	17.69	
BSC	17.80	17.87	17.68	17.75	

Another control to be considered is the weather. It is a well established fact in the literature that weather, especially severe weather, plays a very important role in supermarkets' daily activities. Here, one joint measure of bad weather is tested for inclusion in the model. The next candidate model is called 'Model 4.2', and it is presented in equation (4.3):

$$(4.3) \qquad y_{it} = \alpha + v_i + \beta x_{it} + \sum_{h \in H} \sigma_h s_h + \xi w + \varepsilon_{it},\ i = 1, ..., 67;\ t = 1, ..., 132,$$

where w represents a dummy variable equal to one if weather was bad[20], and ξ is the coefficient to be estimated. H is the set of holidays. Table 4.2 provides comparison of Model 4.2 to Base model, again with two measures of promotional activity.

Table 4.2. Specification Search: Model 4.2

Measures of Goodness-of-Fit	a) Promotional Discounts Ratio				
	Base Model		Model 2		RMSE Ratio (Model 2/Base)
	FE	OLS	FE	OLS	
R-square	0.02264	0.86463	0.14905	0.88214	
Adj. R-square	0.01492	0.86356	0.14123	0.88105	
RMSE	1,773.55	1,773.55	1,655.95	1,655.95	0.9337
AIC	17.79	17.81	17.66	17.67	
BSC	17.79	17.86	17.67	17.74	
Measures of Goodness-of-Fit	b) Price Decrease Ratio				
	Base Model		Model 2		RMSE Ratio (Model 2/Base)
	FE	OLS	FE	OLS	
R-square	0.01263	0.86324	0.14529	0.88161	
Adj. R-square	0.00483	0.86216	0.13743	0.88053	
RMSE	1,782.61	1,782.61	1,659.61	1,659.61	0.9310
AIC	17.80	17.82	17.66	17.68	
BSC	17.80	17.87	17.67	17.74	

Adding the weather dummy variable to the holiday dummy variables helped improve fit. The R-square has not changed a lot incrementally (compared to Model 4.1), but it increases R-square, and decreases RMSE, Akaike and Schwarz Bayesian Information Criteria. Compared to the Base model, fit improved quite a bit. There is a 7 percent decrease in RMSE.

[20] Bad weather could be any of the following: more than 0.5 inches of rain a day, snowfall exceeding 2 inches a day, or any major storm event (tornadoes, thunderstorms, high winds and hail) in a particular week.

The time dimension is still not accounted for in its entirety. The seasonal component is important, and is controlled for by including holiday dummy variables. Another element of time dimension is the trend. 'Model 4.3' tries to implement trend dimension by including individual stores' time trends. Any identified trend breaks are represented by separate coefficients. 'Model 4.3' is represented in equation (4.4):

$$(4.4) \qquad y_{it} = \alpha + \nu_i + \beta x_{it} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it}, \; i = 1, \ldots, 67; \; t = 1, \ldots, 132,$$

where t represents trend, g_{bi} are the coefficients to be estimated, and B is a set of breaks[21]. Including individual trend is expected to improve fit, but must be carefully examined. The comparison of Model 4.3 to Base model is given in Table 4.3.

Table 4.3. Specification Search: Model 4.3

Measures of Goodness-of-Fit	**a) Promotional Discounts Ratio**				
	Base Model		**Model 3**		**RMSE Ratio (Model 3/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.02264	0.86463	0.41049	0.91835	
Adj. R-square	0.01492	0.86356	0.39530	0.91624	
RMSE	1,773.55	1,773.55	1,389.56	1,389.56	0.7835
AIC	17.79	17.81	17.32	17.34	
BSC	17.79	17.86	17.44	17.51	
Measures of Goodness-of-Fit	**b) Price Decrease Ratio**				
	Base Model		**Model 3**		**RMSE Ratio (Model 3/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.01263	0.86324	0.40411	0.91746	
Adj. R-square	0.00483	0.86216	0.38875	0.91534	
RMSE	1,782.61	1,782.61	1,397.07	1,397.07	0.7837
AIC	17.80	17.82	17.33	17.35	
BSC	17.80	17.87	17.46	17.53	

[21] If there was one break in trend for a particular store, it would have two trend coefficients estimated.

A decrease in RMSE is substantial. Including holiday dummies, the weather dummy and individual stores' trends, decreased RMSE by 22 percent. Akaike and Schwarz Bayesian Information Criteria show big decreases, which directly translates to better fit. The R-square shows a big improvement. Compared to the Base model, Model 4.3 has an R-square of 40 percent, which is a value with no individual dummy effect fit included. If group effect is included, R-square is over 91 percent. The incremental change from Model 4.2 to Model 4.3 is also quite substantial – R-square more than doubled, while RMSE, Akaike and Schwarz Bayesian Information Criteria show sizeable decreases. Fit is improved again. Also, the correlation between individual effects and regressors is significant and negative[22]. The augmented regression Hausman test confirms a difference in fixed and random effects estimates. The null hypothesis of no difference is rejected at 1 percent significance level.

Finally, it is worth checking whether or not quadratic trend contributes to better fit even further. 'Model 4.4' adds quadratic trend to Model 4.3, as shown in equation (4.5):

$$(4.5)\qquad y_{it} = \alpha + v_i + \beta x_{it} + \sum_{h\in H} \sigma_h s_h + \xi w + \sum_{b\in B} g_{bi} t + \sum_{b\in B} a_{bi} t^2 + \varepsilon_{it},\ i = 1,\ldots,67;\ t = 1,\ldots,132,$$

where a_{bi} represent the quadratic trend coefficients to be estimated. Table 4.4 contains comparison of Model 4.4 to Base model.

Model 4.4 provides the greatest decrease in RMSE – over 25 percent compared to Base model. Besides this great decrease in RMSE, R-square gained even more. Compared to the Base model there is no doubt that this model provides a better fit to

[22] For Promotional Discounts Ratio it equals -0.26, and for Price Decrease Ratio it is even higher: -0.29.

data. Where some ambiguity develops is in the comparison of Models 3 and 4. In this case, R-square shows improvement, RMSE is lower, and Akaike Information Criterion has a lower value, all showing a better fit. Looking at the Schwarz Bayesian Information Criterion, an opposite conclusion could be drawn. It is well known that the marginal cost of adding regressors is greater with the Schwarz Bayesian Information Criterion than with the Akaike Information Criterion. The former criterion is very ‘conservative’, whereas the other three show significant (incremental) improvement in fit. Nevertheless, the quadratic individual trends would not be a part of the model.

Table 4.4. Specification Search: Model 4.4

Measures of Goodness-of-Fit	**a) Promotional Discounts Ratio**				
	Base Model		**Model 4**		**RMSE Ratio (Model 4/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.02264	0.86463	0.47756	0.92764	
Adj. R-square	0.01492	0.86356	0.45508	0.92452	
RMSE	1,773.55	1,773.55	1,319.09	1,319.09	0.7438
AIC	17.79	17.81	17.23	17.25	
BSC	17.79	17.86	17.47	17.54	
Measures of Goodness-of-Fit	**b) Price Decrease Ratio**				
	Base Model		**Model 4**		**RMSE Ratio (Model 4/Base)**
	FE	**OLS**	**FE**	**OLS**	
R-square	0.01263	0.86324	0.46841	0.92637	
Adj. R-square	0.00483	0.86216	0.44553	0.92320	
RMSE	1,782.61	1,782.61	1,330.59	1,330.59	0.7464
AIC	17.80	17.82	17.25	17.27	
BSC	17.80	17.87	17.49	17.56	

Model 4.3 given in equation (4.4) will be examined and tested, and the results presented in the next chapter. Many important econometric issues have not yet been

addressed. These are groupwise heteroskedasticity, contemporaneous correlation across panels, and autocorrelation within panels, to name a few. The inference would be affected if any of these were found. A completely separate issue would arise if a lagged dependent variable was used in regression. It is worth examining if past realizations of the dependent variable (customer traffic) affect its current level.

5. RESULTS – STATIC MODEL

The effects of retailer's promotional activities on customer traffic will be estimated from the model presented in equation (5.1):

$$(5.1) \qquad y_{it} = \alpha + v_i + \beta x_{it} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it},\ i = 1,...,67;\ t = 1,...,132,$$

where y_{it} represents customer traffic, α is the intercept term, v_i's are store-specific unobserved effects, x_{it} is the measure of retailer's promotional activity (promotional discounts ratio or price decrease ratio), β is the promotional coefficient to be estimated, s_h represents a holiday dummy variable (H is the set of holidays), and σ_h are the coefficients to be estimated, w represents a dummy variable equal to one if weather was bad, ξ is the weather coefficient to be estimated, t represents trend (B is a set of breaks), g_{bi} are trend coefficients to be estimated, and ε_{it} represents idiosyncratic error.

Equation (5.1) represents a static model – there are no lagged variables (dependent or independent) on the right hand side of the equation. The static relationship presents difficulties to the estimation process, but these difficulties are minimal in comparison to the number of obstacles that a dynamic model's estimation presents. These two types of models will be examined independently for clarity of exposition. Based on the available data, the retailer's promotional activity will be examined by means of two different variables – promotional discounts ratio and price decrease ratio. The estimation results will be given separately.

5.1. Promotional Discounts Ratio

The structure of available data is such that the cross sectional dimension is smaller than the time dimension. This is what distinguishes time series cross sectional models from the panel data models[1]. The quality of different estimators directly depends on the asymptotic properties upon which they were derived, so that the dominant dimension – cross section or time – plays an important role. The estimation process starts with the fixed effects estimator applied to equation (5.1). Several diagnostic tests will be run so that all needed corrections, or even different estimators can be employed.

The analysis starts with the promotional discounts ratio as one of the two measures of retailer's promotional activity. Table 5.1 provides results of the first regression. The promotional discounts ratio coefficient shows that an increase in promotional discounts worth one percent of the current week's revenue, holding everything else constant, would increase the store's weekly traffic by 90.71 customers. This coefficient is highly significant. Some caution should be applied when its true meaning is analyzed. There is no way one can check if these are new customers (switching from a competitor), or if they are existing (loyal) customers who decided to visit a store because of an advertised deal. Whatever the case, the effect is positive without a doubt.

All holiday coefficients have expected signs, and they are highly significant, with the exception of President's Day. Clearly, Memorial Day, July 4th, and Thanksgiving Day bring the most customers into stores. Other holidays, such as Halloween and Easter,

[1] The typical panel dataset has a large cross-sectional dimension, and there are just a few available periods.

have positive effects that are smaller than those of the above three holidays. One of the coefficients that has (surprisingly) positive value is Christmas. It is specific because it includes Christmas and New Year's period shopping activity, as well as a short period between the two when a decrease in customer traffic would be expected. Here it is positive at 294.60 customers. It would be much better to have separate coefficients for these two periods, but it is not possible to construct them.

Table 5.1. Promotional Discounts Ratio Estimates: Fixed Effects

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Promotional Discounts Ratio	90.71***	4.29	21.14
President Day	71.48	91.34	0.78
Memorial Day	1,609.73***	83.04	19.38
July 4th	1,303.90***	90.03	14.48
Labor Day	246.58***	78.55	3.14
Halloween	948.50***	75.53	12.56
Thanksgiving Day	1,209.93***	82.02	14.75
Post-Thanksgiving	-2,221.66***	104.59	-21.24
Easter	718.37***	90.57	7.93
Christmas	294.60***	64.61	4.56
No Holiday	177.96***	37.92	4.69
Bad Weather	-260.23***	32.62	-7.98
Constant	19,909.62***	61.07	326.01

R-square (FE)	0.4150	Groups	67
Adjusted R-square (LSDV)	0.9169	Observations	8,557
Correlation of individual effects with regressors	-0.2600	Durbin-Watson	1.8964
Bayesian-Schwarz Criterion	17.4380	Akaike Criterion	17.3135

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Two coefficients have significant negative values. The first one is bad weather. It has negative impact on the store traffic, which is expected. This result shows that including bad weather control was appropriate. If there was just one day in a week with bad weather, some 260 customers would not visit the store, holding everything else constant. Nevertheless, this effect is small when compared to the post Thanksgiving week reduction in customer traffic – on average it's a decrease of 2,221.66 customers.

The promotional discounts ratio coefficient can now be compared with other coefficients' values, because it has clearer meaning when put into perspective. Promotional discounts worth 10 percent of weekly revenue would have a similar effect on store traffic as an average holiday. Although this might seem like a lot in terms of dollar value, these significant promotions are not frequently applied.

Before these results are accepted as final, several tests should be run. It is well known that fixed effects estimator assumes cross sectional (groupwise) homoskedasticity, cross sectional independence in the residuals (no contemporaneous correlation), and no serial correlation in the idiosyncratic errors (no autocorrelation). If the real covariance structure is different from the assumed, standard errors should be very different from the ones given in Table 5.1.

The first potential problem to be checked for is groupwise heteroskedasticity – error variances specific to the cross sectional unit. Variance could be very different for each group (i.e. store) because of their different sizes. In order to test whether this issue exists, a modified Wald statistic[2] for groupwise heteroskedasticity in the residuals of a

[2] Greene (2000, p. 598)

fixed effect regression model can be used. Other available tests – the Lagrange multiplier, likelihood ratio and standard Wald test – depend on the assumption of normally distributed disturbances. When the assumption of normality is violated, the modified Wald statistic[3] is used. It is safe to use this test even if the assumption of normality is not violated. The resulting test statistic is distributed Chi-square under the null hypothesis of homoskedasticity, with degrees of freedom equal to number of groups (cross sections).

Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 3,705.91, which leads to rejection of the null hypothesis. Groupwise heteroskedasticity is present, which means that the standard errors reported in Table 5.1 are incorrect.

Cross-sectional (contemporaneous) correlation is another serious issue that must be addressed if diagnosed in the cross section time series data. Correlation of the disturbances across stores is likely when all of them are influenced by the same macroeconomic factors, as is expected. Another important source of cross sectional correlation is the fact that all the stores belong to the same chain. Any chain-wide decision (as promotion related decisions very often are) has direct consequences for all the stores to somewhat varying degrees.

The Breusch-Pagan Lagrange multiplier statistic for cross sectional independence in the residuals of a fixed effect regression model can be used for testing purposes. This

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[3] $W' = \sum_{i=1}^{n} \frac{\left(\hat{\sigma}_i^2 - \hat{\sigma}^2\right)^2}{V_i}$, where $V_i = \frac{1}{T}\frac{1}{T-1}\sum_{t=1}^{T}\left(e_{it}^2 - \hat{\sigma}_i^2\right)^2$, and $\hat{\sigma}_i^2 = \frac{1}{T}\sum_{t=1}^{T} e_{it}^2$.

statistic tests the hypothesis that the residual correlation matrix, computed over observations common to all cross sectional units, is an identity matrix of order equal to the number of cross sectional units. This test statistic[4] is distributed as Chi-square[5] under the null hypothesis of cross sectional independence. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 92,328.28, which leads to rejection of the null hypothesis of cross sectional independence. This result was expected.

Finally, it's important to know if serial correlation in the idiosyncratic errors exists. Models that contain a lagged dependent variable often face this problem. One consequence of serial correlation is that usual standard errors obtained from fixed effects estimation can be very misleading, i.e. biased. Other estimates would be consistent, but inefficient. A long series (large *T*) could make this problem more pronounced. A common approach used in dealing with serial correlation is the transformation of data[6]. One indication of serial correlation is the Durbin-Watson statistic. If there is no serial correlation, its value will be around 2, and if it falls below 2 there is positive serial correlation. Table 5.1 reports a value of 1.8964, which suggests extremely small positive serial correlation.

Wooldridge (2002, p. 282) developed a test for serial correlation in the idiosyncratic errors. It is based on a first difference estimator. Under the null hypothesis of no first-order serial correlation, the residuals from the regression of the first-

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[4] $BP = T\sum_{i=2}^{n}\sum_{j=1}^{i-1} r_{ij}^2$, where r_{ij}^2 is the *ij*th residual correlation coefficient.

[5] Degrees of freedom equal g*(g – 1)/2, where g is the number of cross-sectional units.

[6] See Baltagi (2005, pp. 84-91) for details.

differenced variables should have an autocorrelation of -0.5. This implies that the coefficient on the lagged residuals, in a regression of the lagged residuals on the current residuals, should be -0.5. Drukker (2003) performed a simulation which shows that this test has good size and power properties in reasonable sample sizes.

The obtained test statistic has value of 0.60, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. Null hypothesis of no first-order serial correlation can be accepted. No lagged dependent variable is among the regressors in equation (5.1), so this result is unsurprising. Serial correlation could arise in dynamic context.

After a series of tests is performed, equation (5.1) estimated by fixed effects estimator shows signs of: (i) groupwise heteroskedasticity, and (ii) contemporaneous correlation. Idiosyncratic error term serial correlation was not found. Estimation results presented in Table 5.1 could be considered unbiased, but certainly not efficient. Obviously this serious inefficiency issue must be resolved in order to provide a basis for correct inference. Standard errors and variance-covariance estimates should be computed, taking into account heteroskedasticity and contemporaneous correlation across panels.

There are three methods that could be used for the estimation and/or inference when heteroskedasticity and contemporaneous correlation across panels are present. One of them is the Feasible Generalized Least Squares (FGLS) estimator. This method is based on the assumption that all aspects of the model are completely specified, in which case it is asymptotically efficient. Its disadvantage is that the standard error estimates are conditional on the estimated disturbance covariance matrix, which is in turn dependent on the assumed covariance structure. If the assumptions are not correct, standard errors will not be correct, and they could be too optimistic[7]. The Feasible Generalized Least Squares estimator requires a balanced dataset and greater time series dimension than a cross sectional one. The latter requirement is fulfilled, but the former is not. Since the available data is not balanced, it is not possible to use this estimation method[8].

Another possible way to treat groupwise heteroskedasticity and contemporaneous correlation across panels is to apply the Panel-Corrected Standard Error (PCSE) estimator. If there is no autocorrelation present this method performs the Ordinary Least Squares parameter estimation. If autocorrelation is specified, method uses Prais-Winsten regression[9], which transforms auto-correlated disturbances into serially uncorrelated classical errors. The Panel-Corrected Standard Error method assumes that disturbances are heteroskedastic and contemporaneously correlated across panels for the purpose of computing standard errors and variance-covariance estimates. This method does not require balanced panels, and so it can be applied to the available data.

The model presented in equation (5.1) was estimated using the Panel-Corrected Standard Error estimator. Since there was no autocorrelation detected in idiosyncratic errors, estimates are obtained from an Ordinary Least Squares regression. Table 5.2 shows that coefficients' values perfectly match those from Table 5.1, but the difference becomes obvious when standard errors are compared. Taking account of groupwise

[7] See Beck and Katz (1995) for details.
[8] Both Stata (-xtgls-) and E-Views required balanced data.
[9] See Baltagi (2005, p. 84) for details.

heteroskedasticity and contemporaneous correlation across panels results in roughly 5 to 6 times greater standard errors. Inference results are very different from those obtained in Table 5.1.

Table 5.2. Promotional Discounts Ratio Estimates: Panel-Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Promotional Discounts Ratio	90.71***	21.64	4.19
President Day	71.48	544.46	0.13
Memorial Day	1,609.73***	487.31	3.30
July 4th	1,303.90***	540.22	2.41
Labor Day	246.58	453.27	0.54
Halloween	948.50**	452.05	2.10
Thanksgiving Day	1,209.93***	490.09	2.47
Post-Thanksgiving	-2,221.66***	621.94	-3.57
Easter	718.37	541.85	1.33
Christmas	294.60	385.03	0.77
No Holiday	177.96	224.74	0.79
Bad Weather	-260.23	192.53	-1.35
Constant	19,909.62***	334.35	59.55
Adjusted R-square (LSDV)	0.9169		
Groups	67	Durbin-Watson	1.8964
Observations	8,557		
Bayesian-Schwarz Criterion	17.5078	Akaike Criterion	17.3289

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

The promotional discounts ratio coefficient remained highly significant, which is the most important result. Several major holidays – Memorial Day, July 4th, and Thanksgiving Day have highly significant coefficients. Another very important effect is that of post Thanksgiving week, which is also highly significant, and negative.

President’s Day and Labor Day coefficients are insignificant, but these are not typically enthusiastic shopping periods in the supermarket industry. A slightly different situation is found for the Easter coefficient, which does not show a highly significant coefficient, but it is over the standard error, and had a p-value of 0.185.

Another unsurprising result is the insignificant coefficient for the Christmas and New Year’s period. This coefficient includes the effects of pre-Christmas, post-Christmas, and New Year shopping periods, which definitely include some deceleration of shopping frenzy. A similar inconclusive effect in a different setup[10] was obtained by Chevalier, Kashyap and Rossi (2003). No-holiday periods also became insignificant, and this result is desirable. Finally, the bad weather coefficient remains significant, and this result is also very important.

Yet another possible method that can be used to handle groupwise heteroskedasticity and contemporaneous correlation across panels is the application of the White cross section method[11]. This method treats the pool regression as a multivariate regression (with one equation for each cross section), and computes White-type robust standard errors for the system of equations. This variance-covariance estimator is robust to contemporaneous correlation, as well as different error variances in each cross section. The White cross section method differs from the Panel-Corrected Standard Errors method because it uses the outer product of the cross sectional residuals instead of an estimate of the cross sectional residual (contemporaneous) covariance matrix in estimating the coefficient covariance estimator.

[10] Seasonal patterns in retail and wholesale price indices, as well as mark-ups.
[11] See Wooldridge (2002, p. 152) for details.

Table 5.3 provides the same coefficient estimates as Tables 5.1 and 5.2, but with a different correction of standard errors. The promotional discounts ratio coefficient remains highly significant again. Memorial Day and July 4th coefficients are highly significant, but the Thanksgiving day coefficient loses some of its significance[12]. The post Thanksgiving week coefficient is highly significant, and negative. Other coefficients did not significantly change in comparison with Table 5.2 results. However, bad weather shows stronger significance.

Table 5.3. Promotional Discounts Ratio Estimates: White Cross Section

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Promotional Discounts Ratio	90.71***	22.84	3.97
President Day	71.48	477.26	0.15
Memorial Day	1,609.73***	399.16	4.03
July 4th	1,303.90***	401.73	3.25
Labor Day	246.58	269.22	0.92
Halloween	948.50**	503.39	1.88
Thanksgiving Day	1,209.93	946.48	1.28
Post-Thanksgiving	-2,221.66***	253.63	-8.76
Easter	718.37	463.39	1.55
Christmas	294.60	588.65	0.50
No Holiday	177.96	220.70	0.81
Bad Weather	-260.23	175.71	-1.48
Constant	19,909.62***	305.57	65.16
Adjusted R-square (LSDV)	0.9169		
Groups	67	Durbin-Watson	1.8964
Observations	8,557		
Bayesian-Schwarz Criterion	17.5078	Akaike Criterion	17.3289

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

[12] Its *p*-value equals 0.20.

The conclusion that could be drawn from the presented results is that promotional discounts do indeed have a positive effect on customer traffic. After controlling for store-specific effects, seasonal and weather patterns, and trends, the remaining independent variation establishes a significant positive relationship between this type of promotional activity and customer traffic. This conclusion does not change after groupwise heteroskedasticity and contemporaneous correlation across panels are accounted for. This is, of course, a static view, and a dynamic context might bring different insights. This is a static model – there are no lagged variables (dependent or independent) on the right hand side of the equation. The static relationship presents some difficulties to the estimation process, but these difficulties are minimal in comparison to the number of obstacles that a dynamic model's estimation presents.

The static model's informative content is somewhat limited. Obviously, no conclusions regarding dynamics and long-term effects can be reached. Another incentive for a completely separate treatment of dynamics is that a whole new series of issues is raised when any lagged variables are added to the regression.

5.2. Price Decrease Ratio

Another constructed measure of retailer's promotional activity is price decrease ratio, and its relationship with customer traffic will be examined. As in the previous case of the promotional discounts ratio, the estimation process starts with the fixed effects estimator applied to equation (5.1), where x_{it} is the price decrease ratio. Three diagnostic tests will be run and all needed corrections employed. Table 5.4 provides results of the first regression.

Table 5.4. Price Decrease Ratio Estimates: Fixed Effects

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Price Decrease Ratio	54.43***	2.91	18.68
President Day	97.52	92.23	1.06
Memorial Day	1,680.50***	83.48	20.13
July 4th	1,378.83***	90.60	15.22
Labor Day	283.73***	79.12	3.59
Halloween	927.37***	75.97	12.21
Thanksgiving Day	1,236.23***	82.56	14.97
Post-Thanksgiving	-2,339.50***	104.50	-22.39
Easter	736.04***	91.17	8.07
Christmas	330.53***	65.35	5.06
No Holiday	186.06***	38.18	4.87
Bad Weather	-254.48***	32.89	-7.74
Constant	19,580.15***	75.26	260.15

R-square (FE)	0.4084	Groups	67
Adjusted R-square (LSDV)	0.9159	Observations	8,557
Correlation of individual effects with regressors	-0.2916	Durbin-Watson	1.9038
Bayesian-Schwarz Criterion	17.4492	Akaike Criterion	17.3247

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

The price decrease ratio coefficient shows that a one percent price decrease, holding everything else constant, would increase a store's weekly traffic by 54.43 customers. An average 10 to 15 percent price decrease would correspond to 545 to 815 more customers, which is quite a large positive effect. This coefficient is highly significant. Again there is no way one can check whether these new customers switch from a competitor's store, or whether the existing (loyal) customers just decided to visit a store because of an advertised deal.

Holiday coefficient estimates have expected signs, and they are highly significant, except for President's Day. Memorial Day, July 4^{th}, and Thanksgiving Day bring the most customers into stores. Two holidays that have positive effects that are smaller than those of the above three holidays are Halloween and Easter. The Christmas coefficient shows positive value at 330.53 customers. Keeping in mind that it includes Christmas and New Year's period shopping activity, with short period between the two when a decrease in customer traffic is imminent, its significance could change after robust standard errors are computed, if needed.

Bad weather has a negative impact on store traffic, which is expected. This coefficient is highly significant, but its influence is just a trace when compared to the post Thanksgiving week. The post Thanksgiving week coefficient shows a very sharp reduction in customer traffic – an average decrease of 2,340 customers. Customers infrequently shop during this week, and it should be used by store managers to prepare well for the next shopping period, and possibly change store layout and apply new planograms[13].

The applied fixed effects estimator assumes cross sectional (groupwise) homoskedasticity, cross sectional independence in the residuals (no contemporaneous correlation), and no serial correlation in the idiosyncratic errors (no autocorrelation). If the real covariance structure is different from the assumed, standard errors should be different from the ones given in Table 5.4, and inference would change considerably. This is why several diagnostic tests should be run.

As in the previous case, groupwise heteroskedasticity tops the list of potential problems that needs to be examined. The source of variation in Price decrease ratio case is very similar to Promotional discounts ratio. Error variance could be very different for each group (store) because of their different sizes. A modified Wald statistic for groupwise heteroskedasticity in the residuals of a fixed effect regression model will be used for testing purposes. The resulting test statistic is distributed Chi-square under the null hypothesis of homoskedasticity, with degrees of freedom equal to the number of groups (cross sections).

Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 3,477.62, which leads to rejection of the null hypothesis. Groupwise heteroskedasticity is present, which means that the standard errors reported in Table 5.4 are incorrect.

Another potential problem is contemporaneous correlation across panels. This type of correlation is possible when all stores are influenced by the same macroeconomic

[13] Planogram design considers shelf management and presentation of the product, for better use of valuable shelf space.

factors, and all of them belong to the same chain. Chain-wide decisions would be a typical source of this correlation, and are expected to be found.

The Breusch-Pagan Lagrange multiplier statistic for cross sectional independence in the residuals of a fixed effect regression model can be used for testing purposes. This test statistic is distributed as Chi-square under the null hypothesis of cross sectional independence. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 92,879.11, which leads to rejection of the null hypothesis of cross sectional independence.

Another source of improper inference is possible serial correlation in the idiosyncratic errors. One consequence of serial correlation is that usual standard errors obtained from fixed effects estimation are biased. Other estimates would be consistent, but inefficient. It is quite standard to search for an indication of serial correlation in the Durbin-Watson statistic. If there is no serial correlation, its value will be around 2, and if it falls below 2 there is positive serial correlation. Table 5.4 reports a value of 1.9038, which suggests extremely small positive serial correlation. Of course this needs to be formally checked.

The formal test that will be used to check for the presence of serial correlation in idiosyncratic term is developed by Wooldridge (2002, p. 282). The obtained test statistic has a value of 0.36, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. Null hypothesis of no first-order serial correlation can be accepted. A dynamic model could produce different results for this test.

After these tests are performed, equation (5.1) estimated by fixed effects estimator, using Price decrease ratio as a measure of retailer's promotional activity, shows signs of: (i) groupwise heteroskedasticity, and (ii) contemporaneous correlation. An idiosyncratic error term serial correlation was not found. The estimation results presented in Table 5.4 are unbiased, but inefficient. This serious issue must be taken care of in order to provide a basis for correct inference. As before, standard errors and variance-covariance estimates should be computed, taking into account heteroskedasticity and contemporaneous correlation across panels.

Two methods will be used for the estimation and inference when heteroskedasticity and contemporaneous correlation across panels are present[14]. The first method applied is the Panel-Corrected Standard Error (PCSE) estimator. Since there was no autocorrelation detected in idiosyncratic errors, estimates are obtained from an Ordinary Least Squares regression. Table 5.5 contains the same coefficient estimates as Table 5.4, but there is an obvious difference in reported standard errors between the two.

The price decrease ratio coefficient stays highly significant after its standard error is corrected, which is again the single most important result. All (supermarket) major holidays – Memorial Day, July 4th, and Thanksgiving Day have highly significant coefficients. The post Thanksgiving week effect is again both highly significant and very negative. The President's Day coefficient remained insignificant, but the Labor Day coefficient became insignificant after the correction. The Easter coefficient is significant, and had a *p*-value of 0.177.

[14] Feasible General Least Squares cannot be used again, because the panels are unbalanced.

The insignificant coefficient for the Christmas and New Year's period was expected due to its construction, as was the case for the promotional discounts ratio. The no-holiday periods' coefficient is insignificant, and this result corresponds to the normal (nearly constant) flow of customers between holidays. Finally, the bad weather coefficient remains significant, and this result is also very important, although its level of significance is not very high (p-value = 0.19).

Table 5.5. Price Decrease Ratio Estimates: Panel-Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Price Decrease Ratio	54.43***	14.43	3.77
President Day	97.52	549.29	0.18
Memorial Day	1,680.50***	490.38	3.43
July 4th	1,378.83***	543.84	2.54
Labor Day	283.73	456.59	0.62
Halloween	927.37**	454.95	2.04
Thanksgiving Day	1,236.23***	493.47	2.51
Post-Thanksgiving	-2,339.50***	623.42	-3.75
Easter	736.04	545.50	1.35
Christmas	330.53	388.83	0.85
No Holiday	186.06	226.30	0.82
Bad Weather	-254.48	194.11	-1.31
Constant	19,580.15***	399.64	48.99
Adjusted R-square (LSDV)	0.9160		
Groups	67	Durbin-Watson	1.9038
Observations	8,557		
Bayesian-Schwarz Criterion	17.5190	Akaike Criterion	17.3401

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Table 5.6. Price Decrease Ratio Estimates: White Cross Section

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Price Decrease Ratio	54.43***	14.07	3.87
President Day	97.52	471.48	0.21
Memorial Day	1,680.50***	403.49	4.16
July 4th	1,378.83***	424.64	3.25
Labor Day	283.73	275.34	1.03
Halloween	927.37**	521.15	1.78
Thanksgiving Day	1,236.23	962.10	1.28
Post-Thanksgiving	-2,339.50***	238.89	-9.79
Easter	736.04*	468.44	1.57
Christmas	330.53	601.40	0.55
No Holiday	186.06	220.31	0.84
Bad Weather	-254.48	176.76	-1.44
Constant	19,580.15***	373.04	52.49
Adjusted R-square (LSDV)	0.9160		
Groups	67	Durbin-Watson	1.9038
Observations	8,557		
Bayesian-Schwarz Criterion	17.5190	Akaike Criterion	17.3401

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

The second method used to handle groupwise heteroskedasticity and contemporaneous correlation across panels is the White cross section method. Table 5.6 provides the same coefficient estimates as tables 4 and 5, but with a different correction of standard errors. The price decrease ratio coefficient remains highly significant. The Memorial Day and July 4th coefficients are highly significant, but Thanksgiving Day loses some of its significance[15]. The post Thanksgiving week coefficient remains highly significant. Other coefficients did not change significantly in comparison to Table 5.5

[15] Its *p*-value equals 0.20.

results, except that the Easter coefficient regained significance. Finally, the bad weather coefficient shows stronger significance here than in Table 5.5.

When a retailer's promotional activity is measured by the price decrease ratio, its strong positive relationship with store traffic is found. Groupwise heteroskedasticity and contemporaneous correlation across panels invalidated inference based on the fixed effects estimator, and required correction of standard errors. Although these (typical) issues were addressed and resolved, lower prices retained a strong positive relationship with customer count. A word of caution is due again – a dynamic model might lead to a different conclusion.

6. DYNAMIC MODEL

The results obtained in the static model established a positive relationship between two different measures of retailer's promotional activity and customer traffic. Several issues, such as groupwise heteroskedasticity, contemporaneous correlation across panels, and serially correlated idiosyncratic errors, were diagnosed and dealt with. The static model's informative content is somewhat limited. Obviously, no conclusions regarding dynamics and long-term effects can be reached. Another incentive for a completely separate treatment of dynamics is that a whole new series of issues is raised when any lagged variables are added to the regression.

The static model is given in equation (6.1):

(6.1) $$y_{it} = \alpha + v_i + \beta x_{it} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it},\ i = 1,...,67;\ t = 1,...,132,$$

where y_{it} represents customer traffic, α is the intercept term, v_i's are store-specific unobserved effects, x_{it} is the measure of retailer's promotional activity (promotional discounts ratio or price decrease ratio), β is the promotional coefficient to be estimated, s_h represents a holiday dummy variable (H is the set of holidays), and σ_h are the coefficients to be estimated, w represents a dummy variable equal to one if weather was bad, ξ is the weather coefficient to be estimated, t represents trend (B is a set of breaks), g_{bi} are trend coefficients to be estimated, and ε_{it} represents idiosyncratic error.

There are several different dynamic models well known in econometric theory. In order to capture the dynamic features of the relationship between promotional activity and store traffic, the most general model is tried first: the Autoregressive Distributed Lag

(ARDL) model. This model adds lags of both dependent and independent variables to other regressors. Equation (6.2) represents the most general Autoregressive Distributed Lag model:

$$(6.2) \qquad y_{it} = \alpha + v_i + \sum_{q=0}^{r} \beta_q x_{i,t-q} + \sum_{p=1}^{s} \varphi_p y_{i,t-p} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it},$$

$$i = 1,...,67;\ t = 1,...,132,$$

where β_q are (lagged) promotional coefficients to be estimated, with q denoting the independent variable lag; φ_p are lagged customer traffic coefficients to be estimated, and p are dependent variable lags.

There has been a lot of confusion in the literature whether or not it is possible and correct to use a fixed effects estimator with lag(s) of dependent variable included. Several important facts should be addressed and clarified. The data used throughout this analysis does not have a panel data structure. Typically, panel data have a large cross sectional dimension, while the time dimension is very small and of one digit order. Panel data estimators rely on cross sectional (N) asymptotics. Time series cross section data have just the opposite structure. The cross sectional dimension is small, but the time dimension is large. Estimators rely on time series (T) asymptotics.

Consider a shortened version of equation (6.2) given in equation (6.3):

$$(6.3) \qquad y_{it} = \alpha + \varphi y_{i,t-1} + v_i + \varepsilon_{it}.$$

If someone uses Ordinary Least Squares to estimate a model with a lagged dependent variable (and no fixed effects), the estimator of this coefficient is inconsistent because the explanatory variable (lagged dependent variable) is positively correlated with the error term (v_i + ε_{it}) due to the presence of (omitted) individual effects. This correlation does not vanish as the cross sectional or time dimension gets larger.

What happens when the within groups estimator is used instead? The mean values of y_{it}, $y_{i,t\text{-}1}$, v_i and ε_{it} across T – 1 observations for each i are obtained, and the original observations are expressed as deviations from these individual means. Transformed equations are then estimated by Ordinary Least Squares. Individual effects are wiped out by the within transformation because the mean of the time-invariant v_i is v_i. Although one source of inconsistency is removed, this transformation induces correlation between the transformed lagged dependent variable and the transformed error term. It introduces all realizations of the disturbances (ε_{i2}, ε_{i3}, …, ε_{iT}) into the error term of the transformed equation for period t.

Following Bond (2002, p. 5), the transformed lagged dependent variable could be written as $y_{i,t-1} - \left(1/(T_i - 1)\right)\left(y_{i1} + ... + y_{it} + ... + y_{i,T-1}\right)$, and the transformed error term obtained as $\varepsilon_{it} - \left(1/(T_i - 1)\right)\left(\varepsilon_{i2} + ... + \varepsilon_{i,t-1} + ... + \varepsilon_{iT}\right)$. The component $-y_{it}/(T_i - 1)$ in the former is correlated with ε_{it} in the latter, and the component $-\varepsilon_{i,t-1}/(T_i - 1)$ in the latter is correlated with $y_{i,t\text{-}1}$ in the former. These leading correlations, both negative, dominate positive correlations between other components such as $-\varepsilon_{i,t-1}/(T_i - 1)$ and $-y_{i,t-1}/(T_i - 1)$, so that the correlation between the transformed lagged dependent variable and the transformed error term is negative. This correlation does not vanish as the cross sectional dimension increases, so that within groups estimator is inconsistent.

In short, the within groups estimator coupled with a lagged dependent variable is inconsistent in panel data case. This is where the difference between panel data and time series cross section data shows up. The contribution of each time period to the individual means becomes negligibly small as the number of time periods gets larger. Consequently, this correlation induced by the within transformation vanishes, and the within groups estimator is consistent in the case of large *T* panels (i.e. times series cross section data).

The whole estimation process depends on the structure of available data. Since it does not have a typical panel data form, many estimators whose consistency relies on cross-sectional dimension (*N*) asymptotics would not have the same properties in time series cross section data structure. The within groups estimator can be used, with some caution though.

6.1. Promotional Discounts Ratio

Using the within groups estimator, a search for the optimal number of lags is performed on equation (6.2), where the maximum number of lags is set at 8 ($p = q = 8$). The first measure of a retailer's promotional activity used is the promotional discounts ratio. Results of the first regression are reported in Table 6.1. Starting with the second lag of the store traffic variable, all the coefficients are highly significant. The promotional discounts ratio coefficients show high significance from the third lag all the way up to eighth, except for the seventh, which is still significant.

The usual issues that arise in any panel-like data have to be checked for. These are: groupwise heteroskedasticity, contemporaneous correlation across panels, and possibly serially correlated idiosyncratic errors. The first test performed is the Modified Wald test for groupwise heteroskedasticity in a fixed effect regression model. Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 3,048.22, which leads to rejection of the homoskedasticity hypothesis. Groupwise heteroskedasticity is present, which means that standard errors reported in Table 6.1 are incorrect.

The Breusch-Pagan Lagrange multiplier statistic for cross sectional independence in the residuals of a fixed effect regression model is the next to be applied. This test statistic is distributed as Chi-square under the null hypothesis of cross sectional independence. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 67,940.92, which leads to rejection of the null hypothesis of cross sectional independence.

Table 6.1. Promotional Discounts Ratio Modeling Estimates: Dynamic Fixed Effects

Dependent variable: **Customer Traffic**	Estimates		Standard Error	t-value
Variables				
Customer Traffic (t-1)	0.0167		0.0119	1.40
Customer Traffic (t-2)	0.0859	***	0.0110	7.81
Customer Traffic (t-3)	0.1024	***	0.0113	9.09
Customer Traffic (t-4)	0.1492	***	0.0113	13.15
Customer Traffic (t-5)	0.1118	***	0.0116	9.63
Customer Traffic (t-6)	0.0446	***	0.0116	3.83
Customer Traffic (t-7)	-0.0392	***	0.0112	-3.51
Customer Traffic (t-8)	0.0339	***	0.0114	2.98
Promotional Discounts Ratio	101.9428	***	4.4743	22.78
Promotional Discounts Ratio (t-1)	-3.2201		4.6888	-0.69
Promotional Discounts Ratio (t-2)	6.0376		4.7327	1.28
Promotional Discounts Ratio (t-3)	-9.0619	**	4.5843	-1.98
Promotional Discounts Ratio (t-4)	-10.1441	**	4.5460	-2.23
Promotional Discounts Ratio (t-5)	-19.6598	***	4.8092	-4.09
Promotional Discounts Ratio (t-6)	16.1954	***	4.6164	3.51
Promotional Discounts Ratio (t-7)	6.5216		4.8036	1.36
Promotional Discounts Ratio (t-8)	26.2047	***	4.6595	5.62
President Day	453.6238	***	94.8735	4.78
Memorial Day	1,613.2000	***	90.3884	17.85
July 4th	830.7270	***	91.5553	9.07
Labor Day	58.3364		77.8545	0.75
Halloween	773.4548	***	81.0675	9.54
Thanksgiving Day	1,007.4420	***	84.9514	11.86
Post-Thanksgiving	-2,463.3420	***	134.5910	-18.30
Easter	1,044.6090	***	94.5844	11.04
Christmas	-148.6685	**	76.6940	-1.94
No Holiday	101.1847	***	40.8757	2.48
Bad Weather	-213.3103	***	35.0049	-6.09
Constant	9,386.2560	***	450.8965	20.82

R-square (FE)	0.4639	Groups	67
Adjusted R-square (LSDV)	0.9258	Observations	7,543
Bayesian-Schwarz Info Criterion	17.3447	Akaike Criterion	17.1913

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Finally, the possible presence of serial correlation in idiosyncratic error terms is tested by Wooldridge's test. The obtained test statistic has a value of 413.93, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. The null hypothesis of no first-order serial correlation cannot be accepted. One consequence of serial correlation is that usual standard errors obtained from the fixed effects estimation are biased. Other estimates would be consistent, but inefficient.

Since all three problems are found, standard errors reported in Table 6.1 cannot be used for inference. If they were used, an optimal model would possibly have 8 lags of both dependent and independent variables. The method used here calculates panel-corrected standard error (PCSE) estimates, where the parameters are estimated by Prais-Winsten regression. Results of this new corrective regression are reported in Table 6.2, and they should be compared to those from Table 6.1.

This correction method is developed by Beck and Katz (1995). When computing the standard errors and the variance-covariance estimates, it assumes that the disturbances are, by default, heteroskedastic and contemporaneously correlated across panels. When it also corrects for the serial correlation in the error terms, the Prais-Winsten regression has two options: (i) a coefficient of the autoregressive process that is common to all the panels, or (ii) a different autoregressive coefficient for each panel. Beck and Katz (1995, p. 640) recommend that serially correlated errors should be corrected assuming a common autoregressive parameter, due to its better efficiency for T below 40. Varying coefficients will be used here because $T = 132$.

It takes just a superficial glance at Table 6.2 to notice incredibly different standard errors. They are approximately five times greater than those in Table 6.1. Now customer traffic lags are significant from the second up to and including the fifth lag. There is no single promotional discounts ratio lag that remained significant after the correction. The eighth lag is slightly above its standard error, but with a *p*-value of 0.18 it should not be included. To formally check if these coefficients are jointly equal to zero, a Wald test is used. The obtained test statistic has a value of 6.00, whereas critical chi-square value at 5 percent significance and 11 degrees of freedom is 19.68. The null hypothesis is accepted, which means that all promotional discounts ratio lags, as well as the last three customer traffic lags, are jointly zero.

The Bayesian Schwarz Information criterion seems to have greater value (17.3865) in Table 6.2, than in Table 6.1 (17.3447), which would suggest that the model in Table 6.2 is less desirable. Nevertheless, these two models' information criteria are not directly comparable, because the model presented in Table 6.2 contains dummy variables, whereas the within groups estimator presented in Table 6.1 does not estimate them.

Clearly, the optimal model contains five lags of customer traffic, and no lags of promotional discounts ratio. The model featuring the promotional discounts ratio that will be tested is given in equation (6.4):

$$(6.4) \qquad y_{it} = \alpha + \nu_i + \beta x_{it} + \sum_{p=1}^{5} \varphi_p y_{i,t-p} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it},$$

$$i = 1, \ldots, 67;\ t = 1, \ldots, 132 .$$

A similar search procedure is applied to another measure of retailer's promotional activity – the price decrease ratio.

Table 6.2. Promotional Discounts Ratio Modeling Estimates:

Dynamic Prais-Winsten Panel Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0353	0.0523	0.67
Customer Traffic (t-2)	0.0561	0.0509	1.10
Customer Traffic (t-3)	0.0890 *	0.0519	1.71
Customer Traffic (t-4)	0.1412 ***	0.0526	2.69
Customer Traffic (t-5)	0.1074 **	0.0527	2.04
Customer Traffic (t-6)	0.0454	0.0524	0.87
Customer Traffic (t-7)	-0.0296	0.0525	-0.56
Customer Traffic (t-8)	0.0448	0.0525	0.85
Promotional Discounts Ratio	98.8044 ***	19.6601	5.03
Promotional Discounts Ratio (t-1)	-8.8020	20.2458	-0.43
Promotional Discounts Ratio (t-2)	7.2683	20.3721	0.36
Promotional Discounts Ratio (t-3)	-8.0519	19.8544	-0.41
Promotional Discounts Ratio (t-4)	-7.6989	19.8140	-0.39
Promotional Discounts Ratio (t-5)	-17.2330	20.3761	-0.85
Promotional Discounts Ratio (t-6)	17.0231	20.0829	0.85
Promotional Discounts Ratio (t-7)	5.8259	20.6682	0.28
Promotional Discounts Ratio (t-8)	26.8897	20.0667	1.34
President Day	372.4489	467.6974	0.80
Memorial Day	1,649.7120 ***	457.9238	3.60
July 4th	855.4671 *	455.8272	1.88
Labor Day	54.0052	381.9259	0.14
Halloween	834.9817 **	391.1235	2.13
Thanksgiving Day	1,050.7210 ***	426.0445	2.47
Post-Thanksgiving	-2,335.9060 ***	665.1490	-3.51
Easter	999.1860 **	465.2788	2.15
Christmas	-132.9100	381.8419	-0.35
No Holiday	110.8048	206.5240	0.54
Bad Weather	-202.6595	179.6354	-1.13
Constant	6,406.2040 ***	1,262.1080	5.08

R-square	0.9533	Groups	67
Estimated Covariances	2,278	Observations	7,543
Bayesian-Schwarz Info Criterion	17.3865	Akaike Criterion	17.1725

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.

Note 2: Individual trend coefficients are not reported due to their number.

6.2. Price Decrease Ratio

Equation (6.2) is used again to search for the optimal number of lags, but the price decrease ratio is used as a measure of promotional activity. Both maximum and starting number of lags are set at 8 ($p = q = 8$). The results of the fixed effect (within groups estimator) regression are reported in Table 6.3. All customer traffic lags coefficients are highly significant. The price decrease ratio lags coefficients show high significance for the first three lags as well as for the eighth. This pattern of significance is different from what was found in case of the promotional discounts ratio.

Since several serious issues were diagnosed for the first measure of promotional activity, one needs to check for groupwise heteroskedasticity, contemporaneous correlation across panels, and serially correlated idiosyncratic errors. The Modified Wald test for groupwise heteroskedasticity in fixed effect regression model provides a test statistic value of 2,863.32, which leads to rejection of the homoskedasticity hypothesis, because chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. Groupwise heteroskedasticity is present, which means that the standard errors reported in Table 6.3 are incorrect.

The Breusch-Pagan Lagrange multiplier statistic for cross sectional independence in the residuals of a fixed effect regression model is the next to be applied. This test statistic is distributed as Chi-square under the null hypothesis of cross sectional independence. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 70,069.77, which leads to rejection of the null hypothesis of cross sectional independence.

Table 6.3. Price Decrease Ratio Modeling Estimates: Dynamic Fixed Effects

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0310***	0.0119	2.61
Customer Traffic (t-2)	0.0819***	0.0110	7.47
Customer Traffic (t-3)	0.0818***	0.0112	7.32
Customer Traffic (t-4)	0.1432***	0.0113	12.69
Customer Traffic (t-5)	0.1018***	0.0115	8.83
Customer Traffic (t-6)	0.0535***	0.0114	4.69
Customer Traffic (t-7)	-0.0400***	0.0111	-3.60
Customer Traffic (t-8)	0.0385***	0.0114	3.39
Price Decrease Ratio	56.2026***	3.0879	18.20
Price Decrease Ratio (t-1)	-6.9719**	3.2626	-2.14
Price Decrease Ratio (t-2)	8.7235***	3.1816	2.74
Price Decrease Ratio (t-3)	-5.6085*	3.0997	-1.81
Price Decrease Ratio (t-4)	-4.1743	3.0147	-1.38
Price Decrease Ratio (t-5)	-0.9030	3.1852	-0.28
Price Decrease Ratio (t-6)	-0.3912	3.0155	-0.13
Price Decrease Ratio (t-7)	4.0722	3.1312	1.30
Price Decrease Ratio (t-8)	13.1672***	3.0592	4.30
President Day	413.5641***	98.7848	4.19
Memorial Day	1,638.5800***	92.6227	17.69
July 4th	866.0684***	93.3258	9.28
Labor Day	120.9538	79.4651	1.52
Halloween	715.0846***	82.9101	8.62
Thanksgiving Day	930.1046***	85.1704	10.92
Post-Thanksgiving	-2,698.7050***	135.2526	-19.95
Easter	963.3204***	96.3542	10.00
Christmas	-150.0333**	77.5327	-1.94
No Holiday	89.7403**	41.4922	2.16
Bad Weather	-264.1901***	35.5960	-7.42
Constant	9,393.3590***	453.8757	20.70

R-square (FE)	0.4489	Groups	67
Adjusted R-square (LSDV)	0.9238	Observations	7,543
Bayesian-Schwarz Info Criterion	17.3723	Akaike Criterion	17.2189

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Wooldridge’s test is used to check for a possible presence of serial correlation in idiosyncratic error terms. The obtained test statistic has a value of 374.69, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. The null hypothesis of no first-order serial correlation cannot be accepted. One consequence of serial correlation is that usual standard errors obtained from fixed effects estimation are biased. Other estimates would be consistent, but inefficient.

All three problems are diagnosed again and standard errors reported in Table 6.3 cannot be used for inference. The method to be used instead calculates panel-corrected standard error (PCSE) estimates, where the parameters are estimated by Prais-Winsten regression. Results of this new corrective regression are reported in Table 6.4.

Table 6.4 contains considerably large standard errors. Compared to Table 6.3, customer traffic lags are significant from the second up to and including the fifth lag. There is no single price decrease ratio lag that remained significant after the correction, although the first regression looked promising. One needs to formally check if these coefficients are jointly equal to zero, and the Wald test is used. The obtained test statistic has a value of 4.30, whereas critical chi-square value at 5 percent significance and 11 degrees of freedom is 19.68. The null hypothesis is accepted, which means that all price decrease ratio lags, as well as the last three customer traffic lags, are jointly zero. Again, the Bayesian Schwarz Information Criterion is not used for comparisons, because the model estimated in Table 6.4 contains group dummies, and they are wiped out by the within transformation and are not estimated in Table 6.3. The optimal model which will be estimated for price decrease ratio is also given by equation (6.4).

Table 6.4. Price Decrease Ratio Modeling Estimates:

Dynamic Prais-Winsten Panel Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0507	0.0525	0.97
Customer Traffic (t-2)	0.0499	0.0510	0.98
Customer Traffic (t-3)	0.0686	0.0521	1.32
Customer Traffic (t-4)	0.1350***	0.0525	2.57
Customer Traffic (t-5)	0.0963*	0.0528	1.82
Customer Traffic (t-6)	0.0541	0.0526	1.03
Customer Traffic (t-7)	-0.0317	0.0525	-0.60
Customer Traffic (t-8)	0.0493	0.0525	0.94
Price Decrease Ratio	54.3415***	13.1051	4.15
Price Decrease Ratio (t-1)	-10.0818	13.4562	-0.75
Price Decrease Ratio (t-2)	8.7745	13.4748	0.65
Price Decrease Ratio (t-3)	-4.8714	13.1293	-0.37
Price Decrease Ratio (t-4)	-2.5123	12.8674	-0.20
Price Decrease Ratio (t-5)	0.6561	13.2760	0.05
Price Decrease Ratio (t-6)	0.5375	12.9232	0.04
Price Decrease Ratio (t-7)	4.5598	13.2406	0.34
Price Decrease Ratio (t-8)	13.9951	12.8454	1.09
President Day	333.6384	481.9913	0.69
Memorial Day	1,678.9730***	468.5150	3.58
July 4th	892.9266**	464.9696	1.92
Labor Day	115.6336	389.5086	0.30
Halloween	782.0448**	399.7011	1.96
Thanksgiving Day	971.3635**	428.8579	2.27
Post-Thanksgiving	-2,572.8630***	669.6863	-3.84
Easter	918.7597**	476.6746	1.93
Christmas	-143.5561	387.8213	-0.37
No Holiday	100.7854	209.6288	0.48
Bad Weather	-253.3565	182.5778	-1.39
Constant	6,520.6130***	1,308.5000	4.98

R-square	0.9548	Groups	67
Estimated Covariances	2,278	Observations	7,543
Bayesian-Schwarz Info Criterion	17.4130	Akaike Criterion	17.1990

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

7. RESULTS – DYNAMIC MODEL

The effects of a retailer's promotional activities on customer traffic will be estimated from the model presented in equation (7.1):

$$(7.1) \qquad y_{it} = \alpha + v_i + \beta x_{it} + \sum_{p=1}^{5} \varphi_p y_{i,t-p} + \sum_{h \in H} \sigma_h s_h + \xi w + \sum_{b \in B} g_{bi} t + \varepsilon_{it},$$

$$i = 1, \ldots, 67;\; t = 1, \ldots, 132\,.$$

where y_{it} represents customer traffic, α is the intercept term, v_i's are store-specific unobserved effects, x_{it} is the measure of retailer's promotional activity (promotional discounts ratio or price decrease ratio), β is the promotional coefficient to be estimated, φ_p are lagged customer traffic coefficients to be estimated, and p are dependent variable lags, s_h represents a holiday dummy variable (H is the set of holidays), and σ_h are the coefficients to be estimated, w represents a dummy variable equal to one if weather was bad, ξ is the weather coefficient to be estimated, t represents trend (B is a set of breaks), g_{bi} are trend coefficients to be estimated, and ε_{it} represents idiosyncratic error.

Equation (7.1) represents a dynamic model – it includes lagged dependent variables on the right hand side of the equation. Including a lagged dependent variable among regressors brings in many econometric challenges, and these have to be approached very carefully. Two methods will be used during the estimation process. Once again, the retailer's promotional activity will be examined by means of two different variables – the promotional discounts ratio and price decrease ratio. The estimation results are given separately.

7.1. Promotional Discounts Ratio

The whole estimation process critically depends on the structure of available data. Since it does not have a typical panel data form, many estimators whose consistency relies on cross-sectional dimension (N) asymptotics would not have the same properties in time series cross section data structure. The within groups estimator can be used, with some caution though. A large time series (T) dimension reduces inconsistency that exists when the within groups estimator is used for very short panels. On the other hand, general method of moments (GMM) estimators pose great computational difficulties due to the number of instruments, which may easily reach several thousand. All these will be examined in detail.

The estimation process starts with the fixed effects estimator applied to equation (7.1), and the results are reported in Table 7.1. Several diagnostic tests will be run so that all needed corrections, and/or different estimators can be employed. All coefficients are significant. Since similar regressions were diagnosed with groupwise heteroskedasticity, contemporaneous correlation and serial correlation, all these need to be checked for.

The first test performed is the Modified Wald test for groupwise heteroskedasticity in fixed effect regression model. Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 3,247.91, which leads to rejection of the homoskedasticity hypothesis.

Next, the Breusch-Pagan Lagrange multiplier statistic for cross-sectional independence in the residuals of a fixed effect regression model is applied.

Table 7.1. Promotional Discounts Ratio Estimates: Dynamic Fixed Effects

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0188 *	0.0112	1.68
Customer Traffic (t-2)	0.1175 ***	0.0098	11.93
Customer Traffic (t-3)	0.1135 ***	0.0103	11.02
Customer Traffic (t-4)	0.1570 ***	0.0104	15.11
Customer Traffic (t-5)	0.0814 ***	0.0107	7.59
Promotional Discounts Ratio	95.8850 ***	4.2582	22.52
President Day	482.7649 ***	88.9345	5.43
Memorial Day	1,610.4540 ***	89.1088	18.07
July 4th	926.9323 ***	89.6369	10.34
Labor Day	169.8650 **	75.5050	2.25
Halloween	865.3688 ***	74.9099	11.55
Thanksgiving Day	991.0062 ***	81.0866	12.22
Post-Thanksgiving	-2,246.3710 ***	127.7876	-17.58
Easter	970.0024 ***	87.4078	11.10
Christmas	209.0252 ***	68.8910	3.03
No Holiday	129.5884 ***	38.3973	3.37
Bad Weather	-223.3987 ***	32.9075	-6.79
Constant	9,720.6380 ***	389.7497	24.94
R-square (FE)	0.4542	Groups	67
Adjusted R-square (LSDV)	0.9253	Observations	7,837
Bayesian-Schwarz Criterion	17.3393	Akaike Criterion	17.2006

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 77,970.21, which leads to rejection of the null hypothesis of cross-sectional independence. The possible presence of serial correlation in idiosyncratic terms is tested by Wooldridge's test. The obtained test statistic has a value of 339.72, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. The null hypothesis of no first-order serial correlation cannot be accepted.

Standard errors reported in Table 7.1 cannot be used for inference because groupwise heteroskedasticity, contemporaneous correlation and serial correlation were diagnosed. These results were expected since they showed up during the specification search process, but they had to be formally checked. Another favorable result is asignificant reduction in Bayesian Schwarz Information Criterion. The static model had a value of 17.4380, whereas this dynamic specification reached a value of 17.3393, which is a big improvement in fit. Another proof that a model with 8 lags was not appropriate is the corresponding value of 17.3447, which is greater and less desirable.

Knowing all the problems this particular model is exposed to, some sort of correction or a different form of estimator has to be applied in order to resolve the problems, and provide basis for inference. There are several possible ways to estimate the model given in equation (7.1): (i) use the Prais-Winsten panel-corrected standard errors estimator; (ii) use the first-differenced two-stage least squares; or (iii) apply the generalized method of moments estimator.

The first method (Prais-Winsten panel-corrected standard errors estimator) was developed by Beck and Katz (1995). When computing the standard errors and the variance-covariance estimates, it assumes that the disturbances are, by default, heteroskedastic and contemporaneously correlated across panels. In this particular case, when it corrects for the serial correlation in the error terms, each panel could have a different autoregressive coefficient. Results of this new corrective regression are reported in Table 7.2.

Table 7.2. Promotional Discounts Ratio Estimates:
Dynamic Prais-Winsten Panel-Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0275	0.0532	0.52
Customer Traffic (t-2)	0.0897*	0.0501	1.79
Customer Traffic (t-3)	0.1022**	0.0520	1.96
Customer Traffic (t-4)	0.1517***	0.0522	2.91
Customer Traffic (t-5)	0.0807	0.0528	1.53
Promotional Discounts Ratio	92.3814***	19.4612	4.75
President Day	415.4058	472.8061	0.88
Memorial Day	1,637.2000***	475.5161	3.44
July 4th	970.4779**	475.4277	2.04
Labor Day	148.6990	392.9246	0.38
Halloween	905.6882**	394.9212	2.29
Thanksgiving Day	1,040.7170**	432.2411	2.41
Post-Thanksgiving	-2,101.4950***	676.6732	-3.11
Easter	922.1259**	467.7951	1.97
Christmas	221.2880	367.7747	0.60
No Holiday	134.6299	206.2846	0.65
Bad Weather	-221.3719	178.5622	-1.24
Constant	6,929.4570***	1,201.0450	5.77

R-square	0.9515	Groups	67
Estimated Covariances	2,278	Observations	7,837
Bayesian-Schwarz Criterion	17.3807	Akaike Criterion	17.1833

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Clearly, standard errors are considerably greater than in Table 7.1. Before any analysis of individual coefficients is done, it is important to compare the obtained Bayesian Schwarz Information Criterion with other models. The static model had a value of 17.5078, and the 8-lag dynamic model had 17.3865. The model estimated and presented in Table 7.2 reached a value of 17.3807, which is the lowest and the most desirable.

Full comparative analysis of all the coefficients will be delayed until other possible estimators are examined. All except the first lag coefficient of customer traffic are significant. A word of caution is needed though: lagged values of customer traffic are not doing any direct explaining; they do not have any causal 'status.' They are used for long-term effect calculations.

The promotional discounts ratio coefficient shows that an increase in promotional discounts worth one percent of the current week's revenue, holding everything else constant, would increase store's weekly traffic by 92.38 customers. This coefficient is highly significant. Some caution should be applied when analyzing its true meaning is analyzed. There is no way one could check whether these are new customers (switching from a competitor), or existing (loyal) customers who decided to visit a store because of an advertised deal. Whatever the case, the effect is undoubtedly positive.

Table 7.3. Long-Run Promotional Discounts Ratio

Long-Run Promotional Discounts Ratio	
Estimate	168.4859
Standard Error	43.1165
Chi-square(1)	15.2700

This is just a short-run effect. The long-run effect could be obtained if this short-run coefficient's value is divided by one minus the summation of customer traffic lags coefficients. As Table 7.3 shows, the obtained value is 168.4859, and its standard error is 43.1165, i.e. it is very significant. The null hypothesis that the value is equal to zero is rejected – obtained chi-square statistic of 15.27 is far above the critical value at 5 percent significance of 3.84. "Long-term" spans a five week period in this model, and this should be emphasized.

There is yet another more intuitive way[1] of interpreting this result. When lagged coefficients' values are summed up, they give 0.4517. This proves to be an average memoried process. Some 54.83 percent of the long-run effect is felt immediately, but the remaining 45.17 percent of it is spread through a five week long period. It seems that promotions have prolonged effects that last until the next promotional peak – the next holiday. Holidays are, more or less, distributed in pretty regular 5 to 6 week points in time. This long-term (total) effect shows that if ten percent of a weekly revenues' value is spent on promotions, there would be a traffic increase worth approximately 8.5 percent of the average weekly traffic (1685/19803).

All holiday coefficients have expected signs. Memorial Day brings the most customers into stores. July 4th, Easter, Halloween and Thanksgiving Day also have positive and very significant effects. Other holidays like President's Day and Labor Day have insignificant coefficients, but correct signs. One of the coefficients that is very specific (and insignificant here) is Christmas. It includes the Christmas and New Year's period shopping activity, as well as the short period between the two when a decrease in customer traffic would be expected. Positive significant value would be a suspect, and the obtained result is good and expected[2]. It would be preferable to have separate

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[1] See Beck and Katz (2004, p. 23).
[2] Chevalier, Kashyap, and Rossi (2003) obtain a similar effect when estimating holiday effects on retail, wholesale prices, and retail margins.

coefficients for these two periods, but it is not possible to construct them.

Two coefficients have significant negative values. The first one is bad weather. It has negative impact on store traffic, which is expected. This result shows that including a bad weather control was appropriate. If there was just one day in a week with bad weather, some 221 customers would not visit the store, holding everything else constant. Nevertheless, this effect is small when compared to the post Thanksgiving week reduction in customer traffic – on average it's a decrease of 2,101.50 customers.

Before any other estimation technique was tried, one more variable was added to the equation (7.1). Namely, the promotional discounts ratio interacted with a joint five-holiday dummy variable, which equals one for Memorial Day, July 4th, Halloween, Thanksgiving Day and Easter. These holidays had highly significant positive values in Table 7.2. The interaction coefficient measures the effect of possible change in promotional activity during five major holidays. The same procedure was applied as in Table 7.2. The interaction term did not affect other estimates, and it was completely insignificant[3]. The promotional discounts ratio does not vary during major holidays, and it remains stable when compared to other non-holiday periods[4].

Another possible estimation method that could be used in the analysis is the first-differenced two-stage least squares (2SLS) estimator. This type of estimator for the autoregressive panel data was first proposed by Anderson and Hsiao (1981, 1982). This instrument variable estimator was developed to provide a consistent starting value for computation of Maximum Likelihood estimators. This estimator also removes individual

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[3] See Appendix A, Table A.1.
[4] See Appendix A, Tables A.3, A.6, and A.7.

effects through the first-differencing of equation (7.2):

(7.2) $y_{it} = \alpha + \varphi y_{i,t-1} + v_i + \varepsilon_{it}$.

What makes this transformation different from the within transformation is that it eliminates the individual effects v_i from the model given by equation (7.3):

(7.3) $\Delta y_{it} = \varphi \Delta y_{i,t-1} + \Delta\varepsilon_{it}$,

but does not introduce all realizations of the disturbances (ε_{i2}, ε_{i3}, …, ε_{iT}) into the error term of the transformed equation for period *t*, as does the within transformation. It then uses differences ($\Delta y_{i,t-2} = (y_{i,t-2} - y_{i,t-3})$), or just levels ($y_{i,t-2}$) as instruments for $\Delta y_{i,t-1} = (y_{i,t-1} - y_{i,t-2})$. These instruments are not correlated with $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$, as long as ε_{it} are not serially correlated. This method leads to consistent but not necessarily efficient estimates of the parameters in the model.

Anderson and Hsiao (1981, p. 604) show that this estimator is consistent for large *N*, fixed *T* panels (i.e. typical panels), and is capable of identifying the autoregressive parameter φ if at least three time series observations are available ($T \geq 3$). This estimator is also consistent in large *T* panels as noted by Bond (2002, p. 7). What is troublesome when considering the usefulness of this estimator is its high inefficiency shown in Monte Carlo experiments run by Beck and Katz (2004). Even large time series dimension does not show a lot of improvement in efficiency. This is why this estimator is abandoned, and its successor is used. It is only presented here because the remainder of analysis builds on its logic.

Arellano and Bond (1991) note that there are many more instruments available. They develop a generalized method of moments estimator. The crucial step in processing this estimator is the identification of all the available instruments. Namely, it should be determined how many lags of dependent variable are valid instruments. Lagged levels are then combined with first differences of the strictly exogenous variables. Instrument matrices can become very large, especially for large T. This proved to be the case here. In order to see how the number of instruments rapidly increases with T, an example will be useful. It closely follows Baltagi (2005, p. 136).

Based on equation (7.3), an example for $t = 3$ can be written:

(7.4) $$y_{i3} - y_{i2} = \varphi\left(y_{i2} - y_{i1}\right) + \left(\varepsilon_{i3} - \varepsilon_{i2}\right)$$

In this particular case y_{i1} is a valid instrument because it is highly correlated with $(y_{i2} - y_{i1})$ and not correlated with $(\varepsilon_{i3} - \varepsilon_{i2})$ as long as ε_{it} are not serially correlated. For $t = 4$ one could write:

(7.5) $$y_{i4} - y_{i3} = \varphi\left(y_{i3} - y_{i2}\right) + \left(\varepsilon_{i4} - \varepsilon_{i3}\right).$$

Now y_{i2} and y_{i1} are valid instruments for $(y_{i3} - y_{i2})$, since neither is not correlated with $(\varepsilon_{i4} - \varepsilon_{i3})$. Clearly, at period T the set of available instruments is $(y_{i1}, y_{i2}, \ldots, y_{i,T\text{-}2})$. This instrumental variable procedure does not account for the differenced error term in equation (7.3). In order to do this additional moment conditions are specified[5].

There are two versions of the Arellano-Bond estimator: one-step and two-step estimators. The two-step estimator is supposedly more efficient. Even one of its authors, Bond (2002, p. 9) suggests that a lot of applied work focused on results from the one-step estimator. He continues to advise that efficiency gains from using two-step estimator are modest. Once the estimation has been done, it is imperative that a test of no

[5] See Arellano and Bond (1991, p. 279), Bond (2002, p. 8), and Baltagi (2005, p. 137) for details.

second order serial correlation for the disturbances of the first differenced equation ($E[\Delta\varepsilon_{it}\ \Delta\varepsilon_{i,t\text{-}2}] = 0$) be carried out. This test (Arellano and Bond (1991, p. 282)) provides information to determine whether or not the estimator is consistent.

The results of this estimator are presented in Table 7.4. The analysis of this table starts with the far right bottom part. It reads that 48 lags of dependent variable were used as instruments. Maximum possible is $(T - p - 2)$ i.e. 125 for this particular data. This would result in instrument matrix of immense dimensions[6]. It is also worth emphasizing that coefficients are calculated on first differences.

Before any analysis is tried, one should be well aware of the result of the test that average auto-covariance in residuals of second order is really zero. This hypothesis is clearly rejected, and this is a good result because it means that coefficient estimates are consistent. If this result happened to be different, there would be no need to continue the analysis, because the inference would be flawed.

The coefficients show very similar results to those found in Table 7.2. Some of them show a higher significance level, though. What is slightly different is the Christmas coefficient which has a negative sign, but it's insignificant, and expected. The promotional discounts ratio is positive and highly significant. Another difference from Table 7.2 is a missing coefficient for the constant term. This is an important feature that needs a short clarification. This model is estimated after it has been first-differenced. Including a constant would be equal to first-differenced trend, but since the model

[6] The reported results are the maximum attainable. This is simply physical limitation of software (Stata 9.1), not hardware.

already contains individual store trends, the constant is excluded to prevent perfect multicollinearity.

Table 7.4. Promotional Discounts Ratio Estimates: Arellano-Bond GMM

Dependent variable: **ΔCustomer Traffic (t)**	Estimates	Standard Error	t-value
Variables			
ΔCustomer Traffic (t-1)	-0.0007	0.0268	-0.03
ΔCustomer Traffic (t-2)	0.0744***	0.0158	4.72
ΔCustomer Traffic (t-3)	0.0900***	0.0184	4.89
ΔCustomer Traffic (t-4)	0.1436***	0.0198	7.27
ΔCustomer Traffic (t-5)	0.0873***	0.0158	5.53
ΔPromotional Discounts Ratio (t)	99.0945***	7.1758	13.81
ΔPresident Day	390.1513***	105.5962	3.69
ΔMemorial Day	1,636.3710***	99.3725	16.47
ΔJuly 4th	991.3264***	62.5345	15.85
ΔLabor Day	187.3169***	62.6878	2.99
ΔHalloween	921.9031***	75.1801	12.26
ΔThanksgiving Day	939.6056***	72.9641	12.88
ΔPost-Thanksgiving	-2,295.4230***	106.8605	-21.48
ΔEaster	870.0033***	67.7139	12.85
ΔChristmas	-89.1716	113.5205	-0.79
ΔNo Holiday	132.2241***	23.6011	5.60
ΔBad Weather	-190.0714***	18.7972	-10.11

Arellano-Bond test of average autocovariance in residuals of order 1	z = -6.62	Observations	7,694
		Groups	67
Arellano-Bond test of average autocovariance in residuals of order 2	z = -0.79	Used lags as instruments	48

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

As mentioned previously, estimating Arellano-Bond models with very large *T* brings about a great computational burden for both software and hardware. Instrument matrix' dimensions are measured in thousands. Since it would be impossible to obtain the estimation results with the full set of instruments available, an experiment was simulated. The idea is that by increasing the number of used instruments one can observe the direction in which the coefficients will eventually converge. It is a very well known result obtained by Alvarez and Arellano (2003, p. 1122) that within groups and General method of moments estimators for a first-order autoregressive model with individual effects are consistent for $T/N \to c$ for $0 < c \leq 2$. The dataset used in this study has a value of this constant equal 1.97 ($T/N = 132/67$), so it fits the description.

Table 7.5. Promotional Discounts Ratio: Arellano-Bond Estimator Simulation

(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Number of Lags Used as Instruments (AB)				Prais-Winsten PCSE[1]
ΔCustomer Traffic (t)	6	12	24	48	
Variables					
ΔCustomer Traffic (t-1)	-0.07	-0.05	-0.02	0.00	0.0275
ΔCustomer Traffic (t-2)	0.03	0.04	0.06	0.07	0.0897
ΔCustomer Traffic (t-3)	0.06	0.07	0.08	0.09	0.1022
ΔCustomer Traffic (t-4)	0.12	0.12	0.13	0.14	0.1517
ΔCustomer Traffic (t-5)	0.08	0.07	0.08	0.09	0.0807
ΔPromotional Discounts Ratio (t)	102.58	101.75	100.70	99.09	92.3814
ΔPresident Day	229.55	260.43	319.58	390.15	415.4058
ΔMemorial Day	1,674.46	1,671.50	1,667.70	1,636.37	1,637.2000
ΔJuly 4th	1,076.32	1,080.82	1,047.61	991.33	970.4779
ΔLabor Day	157.16	181.77	192.21	187.32	148.6990
ΔHalloween	1,022.42	993.00	948.85	921.90	905.6882
ΔThanksgiving Day	1,033.53	994.34	956.82	939.61	1,040.7170
ΔPost-Thanksgiving	-2,008.76	-2,126.69	-2,233.82	-2,295.42	-2,101.4950
ΔEaster	709.04	756.94	823.44	870.00	922.1259
ΔChristmas	-75.18	-97.23	-111.95	-89.17	221.2880
ΔNo Holiday	86.44	109.66	125.72	132.22	134.6299
ΔBad Weather	-167.00	-170.66	-184.81	-190.07	-221.3719

[1] Estimates are not first differences' coefficients. This is the Prais-Winsten Panel-Corrected Standard Error.

Table 7.5 shows results previously obtained in Table 7.2 in its column 6. As the number of instruments increases, the obtained coefficients approach values found in column 6. Practitioners have to limit the number of lags of dependent variable used, and it is useful to know that less demanding estimator – the Prais-Winsten panel-corrected standard errors estimator – performs just as well. Finally, it is worth checking to see if the least difficult estimator as regards computation provides at least similar results.

Many journal articles have been written condemning the usage of fixed effects estimators with lagged dependent variables, neglecting other forms of data besides typical panels with short time dimension. Table 7.6 shows that within groups estimator's results are very close to the other two. There is definitely some bias in this last estimator due to the introduced correlation between the lagged dependent variable and the error term, after within transformation is performed. This bias decreases quickly as the time dimension grows, and can not be considered serious for $T = 132$, which is the case here. The final decision about which estimator to use crucially depends on the time series dimension.

There has been an increased interest in macro panel data methodology recently. The available data with sizeable time-series dimensions redirected the focus of panel data econometricians to a completely neglected area of "large T" panels. It is expected that a whole series of new testing and estimating procedures will be developed and made available in standard econometric software packages.

Table 7.6. Three Estimators Comparison: Promotional Discounts Ratio

Dependent variable: **ΔCustomer Traffic (t)**	Arellano-Bond (48)	Prais-Winsten (PCSE)	Fixed Effects (PCSE)
Variables			
ΔCustomer Traffic (t-1)	0.00	0.0275	0.0188
ΔCustomer Traffic (t-2)	0.07	0.0897	0.1175
ΔCustomer Traffic (t-3)	0.09	0.1022	0.1135
ΔCustomer Traffic (t-4)	0.14	0.1517	0.1570
ΔCustomer Traffic (t-5)	0.09	0.0807	0.0814
ΔPromotional Discounts Ratio (t)	99.09	92.3814	95.8850
ΔPresident Day	390.15	415.4058	482.7649
ΔMemorial Day	1,636.37	1,637.2000	1,610.4540
ΔJuly 4th	991.33	970.4779	926.9323
ΔLabor Day	187.32	148.6990	169.8650
ΔHalloween	921.90	905.6882	865.3688
ΔThanksgiving Day	939.61	1,040.7170	991.0062
ΔPost-Thanksgiving	-2,295.42	-2,101.4950	-2,246.3710
ΔEaster	870.00	922.1259	970.0024
ΔChristmas	-89.17	221.2880	209.0252
ΔNo Holiday	132.22	134.6299	129.5884
ΔBad Weather	-190.07	-221.3719	-223.3987

[1] Estimates are not first differences' coefficients.

Note: Individual trend coefficients are not reported due to their number.

7.2. Price Decrease Ratio

As the analysis was performed for the promotional discounts ratio, it will be re-done for another measure of retailer's promotional activity – the price decrease ratio. The first presented estimation is the fixed effects estimator applied to equation (7.1), and the results are reported in Table 7.7.

Table 7.7. Price Decrease Ratio Estimates: Dynamic Fixed Effects

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0296***	0.0113	2.62
Customer Traffic (t-2)	0.1125***	0.0099	11.31
Customer Traffic (t-3)	0.0974***	0.0104	9.37
Customer Traffic (t-4)	0.1545***	0.0105	14.71
Customer Traffic (t-5)	0.0830***	0.0108	7.65
Price Decrease Ratio	52.7462***	2.8965	18.21
President Day	470.5792***	90.1405	5.22
Memorial Day	1,653.1910***	90.0440	18.36
July 4th	981.3713***	90.7129	10.82
Labor Day	204.0416***	76.4727	2.67
Halloween	817.4528***	75.7524	10.79
Thanksgiving Day	995.7017***	82.0293	12.14
Post-Thanksgiving	-2,434.6030***	128.4036	-18.96
Easter	958.8602***	88.4031	10.85
Christmas	205.2439***	69.8274	2.94
No Holiday	138.7039***	38.8576	3.57
Bad Weather	-233.6272***	33.2917	-7.02
Constant	9,726.7940***	394.6089	24.65

R-square (FE)	0.4422	Groups	67
Adjusted R-square (LSDV)	0.9236	Observations	7,837
Bayesian-Schwarz Info Criterion	17.3611	Akaike Criterion	17.2225

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Every single coefficient is significant. Since in the previous case several problems were found, these results call for diagnostic tests. The first test performed is the Modified Wald test for groupwise heteroskedasticity in the fixed effect regression model. Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 3,133.63, which leads to rejection of the homoskedasticity hypothesis. Next, the Breusch-Pagan Lagrange multiplier statistic for cross-sectional independence in the residuals of a fixed effect regression model is applied. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 79,654.58, which leads to rejection of the null hypothesis of cross-sectional independence. A possible presence of serial correlation in idiosyncratic terms is tested by Wooldridge's test. The obtained test statistic has a value of 340.95, where F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. The null hypothesis of no first-order serial correlation cannot be accepted.

Standard errors reported in Table 7.7 cannot be used for inference because groupwise heteroskedasticity, contemporaneous correlation and serial correlation were diagnosed. It is important to check the Bayesian Schwarz Information Criterion values. The static model had a value of 17.4492, whereas this dynamic specification reached a value of 17.3611, a big improvement in fit. The model with 8 lags was not appropriate because the corresponding value found was 17.3723, which is greater and less desirable.

Treatment of the diagnosed issues is similar to that for the promotional discounts ratio. The first method to be used is the Prais-Winsten panel-corrected standard errors estimator. The standard errors and the variance-covariance estimates are based on the assumed heteroskedastic and contemporaneously correlated disturbances across panels. Correction for the serial correlation in the error terms uses a different autoregressive coefficient for each panel. Results of this new corrective regression are reported in Table 7.8.

Table 7.8. Price Decrease Ratio Estimates:
Dynamic Prais-Winsten Panel-Corrected Standard Error

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0405	0.0537	0.75
Customer Traffic (t-2)	0.0834*	0.0506	1.65
Customer Traffic (t-3)	0.0858*	0.0526	1.63
Customer Traffic (t-4)	0.1482***	0.0527	2.81
Customer Traffic (t-5)	0.0817	0.0533	1.53
Price Decrease Ratio	50.9863***	13.1103	3.89
President Day	406.5020	479.4633	0.85
Memorial Day	1,677.3780***	480.6179	3.49
July 4th	1,024.3290**	480.9870	2.13
Labor Day	183.1808	397.9072	0.46
Halloween	854.2510**	399.6745	2.14
Thanksgiving Day	1,042.1070**	437.1793	2.38
Post-Thanksgiving	-2,290.6420***	681.7094	-3.36
Easter	902.5029**	473.2989	1.91
Christmas	217.3032	372.8064	0.58
No Holiday	141.0077	208.4069	0.68
Bad Weather	-230.2636	180.3833	-1.28
Constant	6,994.2820***	1,219.1280	5.74
R-square	0.9531	Groups	67
Estimated Covariances	2,278	Observations	7,837
Bayesian-Schwarz Criterion	17.4014	Akaike Criterion	17.2041

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Standard errors are greater than in Table 7.7. Another comparison of the obtained Bayesian Schwarz Information Criterion with other models is needed. The static model had a value of 17.5190, and the 8-lag dynamic model had 17.4130. The model estimated and presented in Table 7.8 reached a value of 17.4014, which is the lowest and the most desirable.

All except the first lag coefficient of customer traffic are significant. The price decrease ratio coefficient shows that a one percent price decrease, holding everything else constant, would increase the store's weekly traffic by nearly 51 customers. This highly significant coefficient is just a short-run effect. The long-run effect could be obtained if this short-run coefficient's value is divided by one minus the summation of customer traffic lags coefficients. As Table 7.9 shows, the obtained value is 90.9825, and its standard error is 26.5990, i.e. it is very significant. The null hypothesis that the value is equal to zero is rejected – the obtained chi-square statistic of 11.70 is far above the critical value at 5 percent significance of 3.84. "Long-term" spans a five week period in this model.

Table 7.9. Long-Run Price Decrease Ratio

Long-Run Price Decrease Ratio	
Estimate	90.9825
Standard Error	26.5990
Chi-square(1)	11.7000

When lagged coefficients' values are summed up, they give 0.4396. This proves to be an average memoried process. Some 56.04 percent of the long-run effect of the price decrease is felt immediately, but the remaining 43.96 percent of it is spread through a five week long period. As in the previous case, the prolonged effects of price decreases last until the next promotionally active period – the next holiday. This long-term (total) effect suggests that if there were an average ten percent price decrease, there would be a traffic increase worth approximately 4.6 percent of the average weekly traffic (910/19803).

Holiday coefficients have expected signs. Memorial Day shows the strongest effect. July 4th, Easter, Halloween and Thanksgiving Day also have positive and very significant effects. Other holidays like President's Day and Labor Day have insignificant coefficients and right signs. The Christmas coefficient has positive insignificant value, which is the expected result. The bad weather coefficient has negative value, and although not highly significant, its value is high above standard error. The post Thanksgiving week shows a sharp reduction in customer traffic – an average decrease of 2,290.64 customers. Another coefficient that has insignificant value is a no-holiday coefficient. It picks the effects of periods between holidays, and any high significant positive value would be an undesirable result.

The next estimator to be applied is the Arellano-Bond general method of moments one-step estimator. Results are presented in Table 7.10. Once again, 48 lags of dependent variable were used as instruments. After checking the test result on the average auto-covariance in residuals of second order, it clearly shows that such a hypothesis can be rejected.

Table 7.10. Price Decrease Ratio Estimates: Arellano-Bond GMM

Dependent variable: **ΔCustomer Traffic (t)**	Estimates	Standard Error	t-value
Variables			
ΔCustomer Traffic (t-1)	0.0068	0.0283	0.24
ΔCustomer Traffic (t-2)	0.0689***	0.0166	4.16
ΔCustomer Traffic (t-3)	0.0728***	0.0177	4.11
ΔCustomer Traffic (t-4)	0.1393***	0.0202	6.91
ΔCustomer Traffic (t-5)	0.0866***	0.0161	5.39
ΔPrice Decrease Ratio (t)	53.9481***	4.1101	13.13
ΔPresident Day	380.7835***	107.4525	3.54
ΔMemorial Day	1,686.0120***	97.9466	17.21
ΔJuly 4th	1,048.4110***	65.0059	16.13
ΔLabor Day	208.0223***	63.4461	3.28
ΔHalloween	857.9170***	76.6914	11.19
ΔThanksgiving Day	962.4373***	72.6352	13.25
ΔPost-Thanksgiving	-2,453.6650***	112.0893	-21.89
ΔEaster	856.7623***	67.2491	12.74
ΔChristmas	-61.0944	113.8149	-0.54
ΔNo Holiday	138.1178***	24.0881	5.73
ΔBad Weather	-197.8130***	19.1046	-10.35

Arellano-Bond test of average autocovariance in residuals of order 1	z = -6.60	Observations	7,694
		Groups	67
Arellano-Bond test of average autocovariance in residuals of order 2	z = -0.83	Used lags as instruments	48

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Coefficients show very similar results to those found in Table 7.8. the price decrease ratio is positive and highly significant. Its long-run value will not be calculated, because the inference is based on Table 7.8. Again, when compared to Table 7.2, the coefficient for the constant term is missing, because individual trends are included. After they are first-differenced they look like a constant term, and including a constant would produce perfect multicollinearity.

Table 7.11. Price Decrease Ratio: Arellano-Bond Estimators Simulation

(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Number of Lags Used as Instruments (AB)				Prais-Winsten PCSE[1]
ΔCustomer Traffic (t)	6	12	24	48	
Variables					
ΔCustomer Traffic (t-1)	-0.07	-0.05	-0.02	0.01	0.0405
ΔCustomer Traffic (t-2)	0.02	0.03	0.05	0.07	0.0834
ΔCustomer Traffic (t-3)	0.04	0.05	0.06	0.07	0.0858
ΔCustomer Traffic (t-4)	0.11	0.11	0.12	0.14	0.1482
ΔCustomer Traffic (t-5)	0.07	0.07	0.08	0.09	0.0817
ΔPrice Decrease Ratio (t)	56.94	55.88	55.44	53.95	50.9863
ΔPresident Day	211.53	243.56	307.12	380.78	406.5020
ΔMemorial Day	1,729.82	1,725.25	1,718.54	1,686.01	1,677.3780
ΔJuly 4th	1,150.80	1,148.78	1,110.55	1,048.41	1,024.3290
ΔLabor Day	183.03	205.38	215.80	208.02	183.1808
ΔHalloween	959.68	930.10	886.15	857.92	854.2510
ΔThanksgiving Day	1,061.64	1,019.47	981.97	962.44	1,042.1070
ΔPost-Thanksgiving	-2,160.78	-2,282.62	-2,388.83	-2,453.67	-2,290.6420
ΔEaster	690.09	739.54	808.11	856.76	902.5029
ΔChristmas	-48.55	-71.71	-83.68	-61.09	217.3032
ΔNo Holiday	94.72	116.57	132.23	138.12	141.0077
ΔBad Weather	-174.23	-178.77	-192.37	-197.81	-230.2636

[1] Estimates are not first differences' coefficients.

The promotional discounts ratio model estimated by Prais-Winsten panel-corrected standard errors estimator showed that the Arellano-Bond estimator kept converging as the number of instruments increased. It would be interesting to see if the same pattern exists in the case of the price decrease ratio. The simulation is presented in Table 7.11.

Table 7.12. Three Estimators Comparison: Price Decrease Ratio

(1)	(2)	(3)	(4)
Dependent variable: **ΔCustomer Traffic (t)**	Arellano-Bond (48)	Prais-Winsten (PCSE)	Fixed Effects (PCSE)
Variables			
ΔCustomer Traffic (t-1)	0.0068	0.0405	0.0296
ΔCustomer Traffic (t-2)	0.0689	0.0834	0.1125
ΔCustomer Traffic (t-3)	0.0728	0.0858	0.0974
ΔCustomer Traffic (t-4)	0.1393	0.1482	0.1545
ΔCustomer Traffic (t-5)	0.0866	0.0817	0.0830
ΔPrice Decrease Ratio (t)	53.9481	50.9863	52.7462
ΔPresident Day	380.7835	406.5020	470.5792
ΔMemorial Day	1,686.0120	1,677.3780	1,653.1910
ΔJuly 4th	1,048.4110	1,024.3290	981.3713
ΔLabor Day	208.0223	183.1808	204.0416
ΔHalloween	857.9170	854.2510	817.4528
ΔThanksgiving Day	962.4373	1,042.1070	995.7017
ΔPost-Thanksgiving	-2,453.6650	-2,290.6420	-2,434.6030
ΔEaster	856.7623	902.5029	958.8602
ΔChristmas	-61.0944	217.3032	205.2439
ΔNo Holiday	138.1178	141.0077	138.7039
ΔBad Weather	-197.8130	-230.2636	-233.6272

[1] Estimates are not first differences' coefficients.

Increasing the number of used instruments in the Arellano-Bond estimation method shows the direction in which the coefficients will eventually converge. Table 7.11 shows in its column 6 the results previously obtained in Table 7.8. As was noted in Table 7.5, the Arellano-Bond estimator converges to the Prais-Winsten panel-corrected standard errors estimator results. Finally, it is worth checking to see whether or not the fixed effects estimator provides comparable results. Table 7.12 shows that the within groups estimator's results are very close to the other two. There is definitely some bias in this last estimator due to the introduced correlation between the lagged dependent variable and the error term after the within transformation is performed. Also, serial correlation is not too pronounced, which is why the results are so close. If there were more of the serial correlation, it is very questionable if the column 4 of Table 7.12 would be similar to column 3.

Obtained results should always be compared to other studies if these are available. Hoch, Drèze, and Purk (1994) ran a pricing experiment using a subset of Dominick's Finer Foods stores. The experiment lasted for 16 weeks, and it was performed on 26 product categories. They found no significant change in customer count before and during the test. Experimental average price change was about 3 percent; no actual customer counts are reported. Using the results obtained in Table 7.9, an average 3 percent price decrease amounts to about 153 additional customers, which corresponds to a 0.77 percent short-term increase in terms of average weekly customer count. The traffic increase is four times smaller than the price decrease, which perhaps led them to conclude it was insignificant.

The customer count and price decrease relationship are positive without a doubt, but increasing customer traffic is not a simple, unidirectional, process. Every traffic increase is multidimensional with probable profitability and price-image effects. Not being able to measure those, long-term promotional effects should be considered instead. In this case, an average 3 percent price decrease corresponds to a 1.38 percent total increase in terms of the average weekly customer count. This result is far from insignificant.

A study by Srinivasan, Pauwels, Hanssens, and Dekimpe (2004, p. 617) confirms the dynamic results obtained here. Promotional effects die out during a dust settling period, which is measured in weeks. They also find that promotions have a weak impact on store traffic. Their analysis is based on a subset of brands, not overall promotional activity.

As in the case of the promotional discounts ratio, one more variable was added to the equation (7.1) and the estimation was performed. The price decrease ratio was interacted with a joint five-holiday dummy variable, which equals one for Memorial Day, July 4th, Halloween, Thanksgiving Day and Easter. This interaction coefficient measures the effect of possible change in promotional activity during five major holidays. The same estimation procedure was applied as in Table 7.8. The interaction term did not affect other estimates, and it was insignificant[7]. The price decrease ratio does not vary during major holidays, and it remains stable when compared to other non-holiday periods[8].

The conclusion that could be drawn from this result is that stores "ride" on holiday effects. Customers expect promotions during holidays and they certainly make (a few) good deals. As the promotional discounts ratio case shows, the total burden of promotional activity[9] remains very stable[10] throughout the year. Some items' prices are more heavily cut, but it seems that these are averaged out by other promotions that result in shallower price cuts. It has been observed that the number of promoted items

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[7] See Appendix A, Table A.2.
[8] See Appendix A, Tables A.4, A.8, and A.9.
[9] Measured in terms of current revenues.
[10] The retailer does not experience any promotional activity shocks.

increases during major holidays[11]. This dimension of very visible promotional activity has some influence on consumers too.

Finally, the whole dynamic model specification process, diagnostics, and all the results obtained in Tables 7.2, 7.3, 7.8, and 7.9 are checked for stability with different durational definitions of promotional variables. If the promotional discounts ratio and the price decrease ratio are used in their two, four or six week versions, the obtained results are practically the same.

[11] See Appendix A, Tables A.5, A.10, and A.11.

8. PROFITABILITY ISSUES

Section 3 clearly warned about the constraints that have to be accounted for if the wholesale price data is to be analyzed. The average acquisition cost method is used to compile the profit margins in the dataset, and their value is not a good substitute for the marginal (i.e. replacement) cost. High turnover rates in the supermarket industry could minimize this discrepancy, but no information on them is available. Possible deals with suppliers are especially worrisome. If stores completely deplete their stocks, and then overstock at a lower price, the replacement cost could be high, but the wholesale price would remain at a low level for a while. All of these issues should be kept in mind when any analysis based on the available wholesale and profit data is attempted.

Two variables that are of the essence of this part of the analysis are promotional discounts (PROMDISC) and net revenue (PROFIT). These are not described in Section 3. The equation (8.1) represents total promotional discounts:

$$PROMDISC_{it} = \sum_{j=1}^{J} \sum_{u=1}^{U} \sum_{k \subseteq K} \left(p_{iju,t-k} - p_{ijut} \right) q_{ijut} S_{ijut} \ , \tag{8.1}$$

where p_{ijut} is the price of an item with UPC code u that belongs to category j at store i in week t; $p_{iju,t-k}$ is the pre-promotional price of an item with UPC code u that belongs to category j at store i in week $t-k$, where k is a length of sale period[1]; q_{ijut} is the quantity sold of an item with UPC code u that belongs to category j at store i in week t; and S_{ijut} is an index equal to one if an item with UPC code u that belongs to category j at store i in week t was on sale (feature ad or in-store display).

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[1] The results are not sensitive to different values of k. The only reported results are for the case $k = 6$.

In order to calculate the current week's store profit, the wholesale prices were used. Profit is calculated as in equation (8.2):

$$(8.2) \qquad PROFIT_{it} = \sum_{j=1}^{J}\sum_{u=1}^{U}(p_{ijut} - w_{ijut})q_{ijut} \ ,$$

where p_{ijut} is the price of an item with UPC code u that belongs to category j at store i in week t; w_{ijut} is the wholesale price of an item with UPC code u that belongs to category j at store i in week t; q_{ijut} is the quantity sold of an item with UPC code u that belongs to category j at store i in week t.

The effect of a retailer's promotional activities on total profitability will be estimated from the model presented in equation (8.3):

$$(8.3) \qquad y_{it} = \alpha + v_i + \beta x_{it} + \sum_{h \in H}\sigma_h s_h + \xi w + g1t + g2t^2 + g3t^3 + \varepsilon_{it},$$

$$i = 1,...,67; \ t = 1,...,132 \ ,$$

where y_{it} represents total (all 28 categories) profit at store i in week t, α is intercept term, v_i's are store-specific unobserved effects, x_{it} is the measure of a retailer's promotional activity (promotional discounts), β is the promotional coefficient to be estimated, s_h represents a holiday dummy variable (H is the set of holidays), and σ_h are the coefficients to be estimated, w represents a dummy variable equal to one if weather was bad, ξ is the weather coefficient to be estimated, t, t^2, and t^3 are linear, square and cubed trends respectively, $g1$, $g2$, and $g3$ are trend coefficients to be estimated, and ε_{it} represents idiosyncratic error.

A multinomial trend of the third order is used because the obtained profit data experiences a very strong tilde shaped trend. Another model with store-specific third-order multinomial trends was tested, but the Bayesian Schwarz information criterion worsened quite a bit, and the joint trend for all the stores was applied. The addition of nearly 200 additional regressors was penalized more severely by the Bayesian than by the Akaike criterion (as was the expected and well known result), so that the final specification was based on the former criterion.

Table 8.1. Profit Analysis: Fixed Effects Estimates

Dependent variable: **Profit**	Estimates		Standard Error	t-value
Variables				
Promotional Discounts	0.0995	***	0.01	9.75
President Day	98.1173		198.83	0.49
Memorial Day	-346.6260	**	182.20	-1.90
July 4th	-1,584.0760	***	195.43	-8.11
Labor Day	-1,962.0730	***	170.57	-11.50
Halloween	-606.7657	***	164.05	-3.70
Thanksgiving Day	257.3966		177.32	1.45
Post-Thanksgiving	-2,099.3910	***	227.95	-9.21
Easter	-1,711.3010	***	197.67	-8.66
Christmas	-485.8850	***	143.04	-3.40
No Holiday	-863.0175	***	82.48	-10.46
Bad Weather	849.0245	***	75.27	11.28
Trend	283.8214	***	9.88	28.72
Trend^2	-6.1587	***	0.17	-35.63
Trend^3	0.0293	***	0.00	34.20
Constant	15,104.0200	***	183.55	82.29
R-square (FE)	0.4968		Groups	67
Adjusted R-square (LSDV)	0.7125		Observations	8,557
Bayesian-Schwarz Criterion	18.8660		Akaike Criterion	18.8528

Note: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.

The results presented in Table 8.1 should not be taken as final. The usual issues that arise in any panel-like data have to be checked for in order to be able to make any inference. These are: groupwise heteroskedasticity, contemporaneous correlation across panels, and possibly serially correlated idiosyncratic errors. The first test performed is the Modified Wald test for groupwise heteroskedasticity in fixed effect regression model. Chi-square critical value at 5 percent significance and 67 degrees of freedom equals 87.11. The obtained test statistic value is 790.95, which leads to rejection of the homoskedasticity hypothesis. Groupwise heteroskedasticity is present, which means that the standard errors reported in Table 8.1 are incorrect.

The Breusch-Pagan Lagrange multiplier statistic for cross-sectional independence in the residuals of a fixed effect regression model is the next to be applied. This test statistic is distributed as Chi-square under the null hypothesis of cross-sectional independence. Chi-square critical value at 5 percent significance and 2,211 degrees of freedom equals 2,321.51. The obtained test statistic has a value of 50,844.49, which leads to rejection of the null hypothesis of cross-sectional independence.

Finally, the possible presence of serial correlation in idiosyncratic terms is tested by Wooldridge’s test. The obtained test statistic has a value of 52.92, whereas F critical value at 5 percent significance for 1 and 66 degrees of freedom is 3.99. The null hypothesis of no first-order serial correlation cannot be accepted. One consequence of serial correlation is that usual standard errors obtained from the fixed effects estimation are biased. Other estimates would be consistent, but inefficient.

Since all three problems are found, standard errors reported in Table 8.1 cannot be used for inference. The method used instead calculates panel-corrected standard error

(PCSE) estimates, where the parameters are estimated by Prais-Winsten regression. Results of this new corrective regression are reported in Table 8.2.

Table 8.2. Profit Analysis: Prais-Winsten Panel Corrected Standard Errors Estimator

Dependent variable: **Profit**	Estimates	Standard Error	t-value
Variables			
Promotional Discounts	0.0823**	0.04	1.89
President Day	33.5586	1,051.82	0.03
Memorial Day	-534.4989	932.15	-0.57
July 4th	-1,324.8460	1,048.72	-1.26
Labor Day	-1,955.5990***	866.01	-2.26
Halloween	-650.7908	863.37	-0.75
Thanksgiving Day	117.2153	946.35	0.12
Post-Thanksgiving	-2,500.9320**	1,103.86	-2.27
Easter	-1,572.0450	1,052.42	-1.49
Christmas	-727.2182	798.02	-0.91
No Holiday	-903.6571**	397.09	-2.28
Bad Weather	799.9941***	338.56	2.36
Trend	287.9775***	59.71	4.82
Trend^2	-6.2463***	1.06	-5.89
Trend^3	0.0298***	0.01	5.62
Constant	12,270.8800***	975.61	12.58

Adjusted R-square (LSDV)	0.7127	Groups	67
		Observations	8557
Bayesian-Schwarz Criterion	18.8138	Akaike Criterion	18.7462

Note: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.

Many coefficients which seemed to be significant in Table 8.1 do not maintain this significance after the corrections for groupwise heteroskedasticity, contemporaneous correlation, and serial correlation are applied. The most important result found in Table 8.2 is a positive effect of promotional discounts on the store profit. This result implies that for every dollar of promotional discounts, net revenue increases by 8 cents.

Seasonal, weather and trend controls ensure that this result is a pure effect of promotional activity on store profit. Almost all major holidays have insignificant coefficients, which would mean that stores do not lose money during these promotionally intense periods. The exceptions are Labor Day and to some extent July 4th and Easter. Bad weather has a positive effect on profit. One possible explanation could be that customers who manage to go shopping probably purchase only necessary, less promoted (higher margin), items. Post-Thanksgiving has negative effect, and this is the week with lowest customer count throughout the year.

The only result that is difficult to explain is a negative (and significant) value of the no-holiday coefficient. It is really difficult to find its true meaning, but one possible explanation could be based on the work of Vanhuele and Drèze (2002). People have a good working knowledge of the prices charged, and they are able to find good deals (including non-holiday periods). The more promoted items are purchased, the smaller profit is earned, since these items have low margins. It could be the case that this effect is captured by the no-holiday dummy variable, but no one can be absolutely sure. Its high significance means that it definitely belongs to this model. Other seasonal controls are also very important and contribute to the high adjusted R-square value of 0.71.

9. CONCLUSION

It is usually assumed in the literature that the retailer's promotional activities serve the purpose of attracting customers into stores. This assumption lacks empirical verification. The relationship between promotional activity and customer count is examined empirically in just a few studies, and no significantly positive association is found. This dissertation presents a comprehensive empirical study of a unique dataset, which contains customer count data and limited information on the retailer's promotional activity. An extensive processing of the data was performed, and an indirect measure of the promotional activity was obtained. This measure is based on the difference between the pre-promotional period's price and the price charged during the promotion. Two variables are constructed based on the promotional discounts. The first is the promotional discounts ratio, which measures the retailer's promotional effort as a fraction of the current revenue. The second is the price decrease ratio, which is the weighted average of the promotional price cuts. The direct manifestation of the retailer's promotional activity is the sale phenomenon, which is a temporary price reduction followed by a similarly sized price increase. In terms of sales duration, the longest acceptable promotion can last up to 6 weeks.

Two basic models are developed in this dissertation. The static model serves as a reference for two kinds of concerns: (i) the inclusion of the lagged dependent variable which might result in inconsistent estimates, and (ii) the inclusion of the lagged dependent variable to improve fit when nothing else works. The dynamic model makes long-term analysis possible, because it provides enough information to calculate the total effect of the retailer's promotional activity. The data used is not of a typical panel data form. It has a time series cross sectional form with the time dimension exceeding the cross sectional by a factor of 1.97 (N = 67, T = 132). The estimation of a model that contains a lagged dependent variable does not necessarily yield inconsistency for large T datasets, a fact that is not sufficiently recognized. This dissertation outlined several methodologically sensitive problems for reference purposes.

The retailer's promotional activities are positively related to customer count. The average weekly customer count, found in the data, is 19,803. At the average value of the promotional discounts ratio of 7.85 percent, the incremental customer traffic would be equivalent to 712.07 customers. This effect is comparable to an average holiday effect. The price decrease ratio's average value of 18.79 percent corresponds to 1,022.74 additional customers, which is a large positive effect. The long-run effect is even more significant. The promotional discounts ratio at its average value corresponds to a customer traffic total increase of 1,322, whereas the price decrease ratio's long-run contribution reaches 1,709 customers. Roughly, some 55 percent of the long-run effect is felt immediately, but the remaining 45 percent is spread over a five week long period. It seems that promotions have prolonged effects that last until the next promotional peak – the next holiday. Holidays are, more or less, distributed at regular points in time, 5 to 6 weeks apart.

The dataset which is used in the analysis contains recoverable wholesale prices. Any profitability analysis should accept a caveat of the average acquisition cost used in the data assembling process. No replacement cost data is available, but high turnover rates in the supermarket industry provide some level of confidence that the profitability could be examined. It is found that promotional discounts have a positive significant effect on store profit. The result implies that for every dollar of promotional discounts, net revenue increases by 8 cents.

Finally, it might be useful to summarize the results of this dissertation in two statements: (i) retailer’s promotional activity does have a positive impact on the store traffic and it is profitable; and (ii) effects of the promotions extend over a five week long period.

REFERENCES

Alvarez, J., and M. Arellano (2003): “The Time Series and Cross-Section Asymptotics of Dynamic Panel Data Estimators,” *Econometrica*, 71, 1121-1159.

Anderson, T. W., and C. Hsiao (1981): “Estimation of Dynamic Models with Error Components,” *Journal of American Statistical Association*, 76, 598-606.

______ (1982): “Formulation and Estimation of Dynamic Models using Panel Data,” *Journal of Econometrics*, 18, 47-82.

Arellano, M., and S. R. Bond (1991): “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies*, 58, 277-297.

Arnold, S. J., T. H. Oum, and D. J. Tigert (1983): “Determinant Attributes in Retail Patronage: Seasonal, Temporal, Regional, and International Comparisons,” *Journal of Marketing Research*, 20, 149-157.

Baltagi, B. H. (2005): *Econometric Analysis of Panel Data,* 3rd ed., New York: Wiley.

Beck, N., and J. N. Katz (1995): “What to Do (and Not to Do) with Time-Series Cross-Section Data,” *American Political Science Review*, 89, 634-647.

______ (2004): “Time-Series-Cross-Section Issues: Dynamics, 2004,” working paper, New York University. Department of Politics.

Blattberg, R. C., R. Briesch, and E. J. Fox (1995): “How Promotions Work,” *Marketing Science*, 14, G122-G132.

Bliss, C. (1988): “A Theory of Retail Pricing,” *The Journal of Industrial Economics*, 36, 375-391.

Bond, S. R. (2002): “Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice,” working paper, Institute for Fiscal Studies. Nuffield College.

Brown, F. E. (1969): “Price Image Versus Price Reality,” *Journal of Marketing Research*, 6, 185-191.

Chevalier, J. A., A. K. Kashyap, and P. E. Rossi (2003): “Why Don’t Prices Rise During Periods of Peak Demand? Evidence from Scanner Data,” *American Economic Review*, 93, 15-37.

Chintagunta, P. K. (2002): “Investigating Category Pricing Behavior at a Retail Chain,” *Journal of Marketing Research*, 39, 141-154.

Conlisk, J., E. Gerstner, and J. Sobel (1984): “Cyclic Pricing by a Durable Monopolist,” *The Quarterly Journal of Economics*, 99, 489-505.

Decennial US Census Online, U.S. Census Bureau, <http://factfinder.census.gov> (Accessed on: December 5, 2003).

DeGraba, P. (2003): “Volume Discounts, Loss Leaders, and Competition for More Profitable Customers”, Federal Trade Commission Bureau of Economics Working Paper No. 260.

Dominick's Database, the James M. Kilts Center, Graduate School of Business, University of Chicago, <http://gsbwww.uchicago.edu/kilts/research/db/dominicks> (Accessed on: October 22, 2003).

Drèze, X. (1999): “Rehabilitating Cherry-Picking,” working paper, University of Southern California. Marshall School of Business.

Drukker, D. M. (2003): “Testing for serial correlation in linear panel-data models,” *Stata Journal* 3, 168-177.

Enders, W. (1995): *Applied Econometric Time Series*, New York: Wiley.

Feichtinger, G., A. Luhmer, and G. Sorger (1988): “Optimal Price and Advertising Policy for a Convenience Goods Retailer,” *Marketing Science*, 7, 187-201.

Friedman, J. W. (1983): “Advertising and Oligopolistic Equilibrium,” *The Bell Journal of Economics*, 14, 464-473.

Greene, W. H. (2000): *Econometric Analysis*, 4th ed., New York: Prentice Hall.

Grover, R., and V. Srinivasan (1992): “Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments,” *Journal of Marketing Research*, 29, 76-89.

Hess, J. D., and E. Gerstner (1987): “Loss Leader Pricing and Rain Check Policy,” *Marketing Science*, 6, 358-374.

Hoch, S. J., X. Drèze, and M. E. Purk (1994): “EDLP, Hi-Lo, and Margin Arithmetic,” *Journal of Marketing*, 58, 16-27.

Hoch, S. J., B-D. Kim, A. L. Montgomery, and P. E. Rossi (1995): “Determinants of Store-Level Price Elasticity,” *Journal of Marketing Research*, 32, 17-29.

Hosken, D., and D. Reiffen (2001): “Multiproduct Retailers and the Sale Phenomenon,” *Agribusiness*, 17, 115-137.

______ (2004a): “How Retailers Determine Which Products Should Go on Sale: Evidence From Store-Level Data,” *Journal of Consumer Policy*, 27, 141-177.

______ (2004b): “Patterns of Retail Price Variation,” *The Rand Journal of Economics*, 35, 128-146.

Hosken, D., D. Matsa, and D. Reiffen (2001): “Pricing Dynamics of Multiproduct Retailers,” *Advances in Applied Microeconomics*, 10, 129-153.

Hsiao, C. (2003): *Analysis of Panel Data*, 2nd ed., Cambridge: Cambridge University Press.

Kumar, V., and R. P. Leone (1988): “Measuring the Effect of Retail Store Promotions on Brand and Store Substitution,” *Journal of Marketing Research*, 25, 178-185.

Lal, R., and C. Matutes (1994): “Retail Pricing and Advertising Strategies,” *The Journal of Business*, 67, 345-370.

Levy, D., G. Muller, S. Dutta, and M. Bergen (2005): “Holiday Price Rigidity and Cost of Price Adjustment,” *Managerial and Decision Economics*, forthcoming.

MacDonald, J. M. (2000): “Demand, Information, and Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?” *The Journal of Industrial Economics*, 48, 27-45.

NCDC Climate Data Online. National Oceanic & Atmospheric Administration (NOAA), the National Climatic Data Center website, <http://cdo.ncdc.noaa.gov/CDO/cdo> (Accessed on: July 26, 2005).

NCDC Storm Event database, National Oceanic & Atmospheric Administration (NOAA), the National Climatic Data Center website, <http://www7.ncdc.noaa.gov/IPS> (Accessed on: July 26, 2005).

Nielsen Marketing Research (1992): *Category Management: Positioning Your Organization to Win*. Chicago: NTC Publishing Group.

Pesendorfer, M. (2002): “Retail Sales. A Study of Pricing Behavior in Supermarkets,” *The Journal of Business*, 75, 33-66.

Simester, D. (1995): “Signalling Price Image Using Advertised Prices,” *Marketing Science*, 14, 166-188.

Sobel, J. (1984): “The Timing of Sales,” *The Review of Economic Studies*, 51, 353-368.

Srinivasan, S., K. Pauwels, D. M. Hanssens, and M. G. Dekimpe (2004): “Do Promotions Benefit Manufacturers, Retailers, or Both,” *Management Science*, 50, 617-629.

Vanhuele, M., and X. Drèze (2002): “Measuring the Price Knowledge Shoppers Bring to the Store,” *Journal of Marketing*, 66, 72-85.

Varian, H. R. (1980): “A Model of Sales,” *The American Economic Review*, 70, 651-659.

Walters, R. G., and H. J. Rinne (1986): “An Empirical Investigation into the Impact of Price Promotions on Retail Store Performance,” *Journal of Retailing*, 62, 237-266.

Walters, R. G., and S. B. MacKenzie (1988): “A Structural Equations Analysis of the Impact of Price Promotions on Store Performance,” *Journal of Marketing Research*, 25, 51-63.

Warner, E. J., and R. B. Barsky (1995): “The Timing and Magnitude of Retail Store Markdowns: Evidence from Weekends and Holidays,” *The Quarterly Journal of Economics*, 110, 321-352.

Wiggins, V., "Re: st: hausman and xthausman after panel fe, re - DROPPED MEAN/DIFF," 26 Aug 2005, <http://www.stata.com/statalist/archive/2005-08/msg00853.html> (Accessed on: January 16, 2006).

Wooldridge, J. M. (2002): *Econometric Analysis of Cross Section and Panel Data*. Cambridge: MIT Press.

Supplemental Sources

Arellano, M. (2003): *Panel Data Ecoonometrics.* New York: Oxford University Press.

Cameron, A. C., and P. K. Trivedi (2005): *Microeconometrics: Methods and Applications.* New York: Cambridge University Press.

Johnston, J., and J. DiNardo (1997): *Econometric Methods*, 4th ed., New York: McGraw-Hill.

Quantitative Micro Software. (2006): *Eviews for Windows: Release 5.1*. Irvine: QMS.

SPSS Inc. (2004): *SPSS for Windows: Release 13.0.1*. Chicago: SPSS Inc.

StataCorp. (2005): *Stata Statistical Software: Release 9.* College Station: StataCorp LP.

APPENDIX A

Table A.1. Promotional Discounts Ratio Interacted

Dependent variable: **Customer Traffic**	Estimates	Standard Error	t-value
Variables			
Customer Traffic (t-1)	0.0274	0.0533	0.51
Customer Traffic (t-2)	0.0897 *	0.0501	1.79
Customer Traffic (t-3)	0.1022 **	0.0521	1.96
Customer Traffic (t-4)	0.1517 ***	0.0521	2.91
Customer Traffic (t-5)	0.0807	0.0529	1.53
Promotional Discounts Ratio (PDR)	92.3921 ***	20.4468	4.52
President Day	415.4134	473.0716	0.88
Memorial Day (h1)	1,638.0210 ***	650.1603	2.52
July 4th (h2)	971.1175 *	605.3759	1.60
Labor Day	148.5660	393.0609	0.38
Halloween (h3)	906.4250 *	540.3274	1.68
Thanksgiving Day (h4)	1,041.2080 *	564.9412	1.84
Post-Thanksgiving	-2,101.5710 ***	676.8836	-3.10
Easter (h5)	922.7409 *	572.8302	1.61
Christmas	221.3680	367.8273	0.60
No Holiday	134.5543	206.2875	0.65
Bad Weather	-221.4129	178.6351	-1.24
PDR X ((h1)&(h2)&(h3)&(h4)&(h5))	-0.0838	46.8373	0.00
Constant	6,930.7610 ***	1,203.2020	5.76

R-square	0.9515	Groups	67
Estimated Covariances	2,278	Observations	7,837
Bayesian-Schwarz Criterion	17.3818	Akaike Criterion	17.1836

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Table A.2. Price Decrease Ratio Interacted

Dependent variable: **Customer Traffic**	Estimates		Standard Error	t-value
Variables				
Customer Traffic (t-1)	0.0429		0.0536	0.80
Customer Traffic (t-2)	0.0845	*	0.0505	1.67
Customer Traffic (t-3)	0.0815		0.0526	1.55
Customer Traffic (t-4)	0.1456	***	0.0526	2.77
Customer Traffic (t-5)	0.0839		0.0532	1.58
Price Decrease Ratio (PDR)	55.0059	***	13.8054	3.98
President Day	423.5096		478.2329	0.89
Memorial Day (h1)	2,491.0780	***	871.0853	2.86
July 4th (h2)	1,753.0110	**	800.7845	2.19
Labor Day	195.0597		396.6487	0.49
Halloween (h3)	1,646.1170	**	795.3198	2.07
Thanksgiving Day (h4)	1,788.7350	**	787.9129	2.27
Post-Thanksgiving	-2,269.6290	***	680.0524	-3.34
Easter (h5)	1,583.7710	**	775.5896	2.04
Christmas	227.0921		371.6161	0.61
No Holiday	142.6837		207.8604	0.69
Bad Weather	-238.5682		179.9484	-1.33
PDR X ((h1)&(h2)&(h3)&(h4)&(h5))	-39.2317		34.9539	-1.12
Constant	6,888.3550	***	1,218.2480	5.65

R-square	0.9534	Groups	67
Estimated Covariances	2,278	Observations	7,837
Bayesian-Schwarz Criterion	17.3995	Akaike Criterion	17.2013

Note 1: *, **, and *** mean that coefficients are statistically significant at 10%, 5%, and 1% significance level, respectively.
Note 2: Individual trend coefficients are not reported due to their number.

Table A.3. Promotional Discounts Ratio: Deviations from No-Holiday

Promotional Discounts Ratio	**Mean**	**Deviation from No Holiday**
President Day	6.06	-1.87
Memorial Day	9.47	1.55
July 4th	8.64	0.71
Labor Day	7.49	-0.43
Halloween	8.40	0.47
Thanksgiving Day	8.26	0.33
Post-Thanksgiving	3.92	-4.01
Easter	7.05	-0.88
Christmas	7.35	-0.58
No Holiday	7.93	
All Observations	7.99	

Table A.4. Price Decrease Ratio: Deviations from No-Holiday

Price Decrease Ratio	**Mean**	**Deviation from No Holiday**
President Day	15.58	-4.33
Memorial Day	21.11	1.21
July 4th	19.36	-0.55
Labor Day	18.26	-1.65
Halloween	20.65	0.74
Thanksgiving Day	19.50	-0.41
Post-Thanksgiving	14.47	-5.44
Easter	17.34	-2.57
Christmas	17.93	-1.98
No Holiday	19.91	
All Observations	19.68	

Table A.5. Number of Promoted Items: Deviations from No-Holiday

Number of Promoted Items	Mean	Deviation from No Holiday
President Day	429.27	-4.35
Memorial Day	476.17	42.54
July 4th	409.25	-24.37
Labor Day	451.78	18.16
Halloween	445.30	11.68
Thanksgiving Day	479.55	45.92
Post-Thanksgiving	360.86	-72.77
Easter	471.40	37.77
Christmas	482.04	48.41
No Holiday	433.63	

Table A.6. Promotional Discounts Ratio by Category and by Holiday

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas	No Holiday
Analgesics	0.88	0.85	1.39	0.65	0.93	0.91	0.57	1.60	0.74	1.60
Bath Soap	0.77	2.20	2.31	1.23	1.13	1.48	1.16	0.11	0.75	3.26
Beer	4.18	9.35	7.61	8.53	7.24	6.91	6.68	5.22	7.09	5.87
Bottled Juices	1.61	5.03	3.75	3.86	8.55	3.40	0.63	1.57	3.41	4.78
Cereals	1.35	3.36	2.40	4.22	2.10	2.70	0.62	6.44	1.84	2.59
Cheeses	2.88	3.57	4.78	4.55	2.59	9.06	3.70	6.45	6.49	3.41
Cookies	4.41	3.46	2.92	5.61	11.13	3.69	0.77	5.39	1.15	8.18
Crackers	2.41	1.68	1.42	1.96	14.36	2.46	2.35	1.52	2.07	5.45
Canned Soup	1.37	0.12	0.32	0.65	4.69	4.16	0.71	2.12	2.77	3.31
Dish Detergent	4.24	0.74	1.39	3.55	6.86	1.66	1.74	5.99	2.37	3.43
Front-end Candies	0.19	0.72	1.96	5.96	0.35	1.12	1.00	0.57	1.01	1.79
Frozen Dinners	4.82	4.24	16.17	2.39	14.58	6.63	19.31	2.09	4.16	13.11
Frozen Entrees	2.96	43.44	2.69	3.01	6.29	4.45	0.14	4.94	5.06	19.64
Frozen Juices	17.52	10.99	13.60	8.95	15.52	8.02	2.92	12.59	9.74	9.05
Fabric Softeners	2.31	1.84	3.05	1.87	3.40	2.95	0.73	1.99	1.32	3.16
Grooming Products	1.57	1.90	0.90	1.13	1.22	0.80	0.47	1.38	0.82	1.47
Laundry Detergents	7.14	5.75	5.43	2.81	5.65	13.54	0.99	6.09	2.14	6.88
Oatmeal	6.52	0.00	0.39	6.56	2.13	3.37	0.86	0.30	1.90	2.23
Paper Towels	4.40	4.78	6.11	3.30	7.41	2.04	3.47	1.43	2.15	3.71
Refrigerated Juices	17.81	8.71	18.77	14.29	14.29	13.52	3.60	9.65	9.50	11.49
Soft Drinks	12.27	19.05	20.98	19.78	17.40	18.87	11.85	16.85	21.58	16.75
Shampoos	3.05	1.99	2.95	1.38	3.96	2.99	1.47	1.54	1.98	3.07
Snack Crackers	2.45	10.33	3.72	6.57	3.99	8.47	6.15	4.01	12.84	2.57
Soaps	3.01	2.65	1.77	1.93	4.93	3.49	1.96	2.96	3.28	2.25
Toothbrushes	6.77	0.50	2.88	3.38	3.82	2.48	1.19	3.56	1.39	3.70
Canned Tuna	1.13	3.01	2.11	4.27	2.99	1.76	1.97	3.73	1.75	8.30
Toothpastes	1.87	5.79	5.60	4.79	2.58	2.99	2.72	2.77	1.65	3.49
Bathroom Tissues	9.40	3.44	3.75	5.72	13.33	3.65	1.41	5.19	1.64	11.39
ALL	6.06	9.47	8.64	7.49	8.40	8.26	3.92	7.05	7.35	7.93

Table A.7. Promotional Discounts Ratio Deviations from No-Holiday by Category

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas
Analgesics	-0.72	-0.74	-0.20	-0.95	-0.67	-0.69	-1.02	0.00	-0.86
Bath Soap	-2.49	-1.06	-0.95	-2.03	-2.13	-1.78	-2.10	-3.15	-2.51
Beer	-1.69	3.47	1.74	2.66	1.36	1.04	0.80	-0.65	1.22
Bottled Juices	-3.18	0.25	-1.03	-0.92	3.77	-1.38	-4.15	-3.21	-1.38
Cereals	-1.24	0.78	-0.19	1.63	-0.49	0.11	-1.97	3.85	-0.75
Cheeses	-0.53	0.16	1.38	1.14	-0.82	5.65	0.29	3.04	3.08
Cookies	-3.78	-4.72	-5.26	-2.58	2.95	-4.49	-7.42	-2.80	-7.03
Crackers	-3.04	-3.77	-4.03	-3.49	8.91	-2.98	-3.10	-3.93	-3.37
Canned Soup	-1.94	-3.18	-2.99	-2.66	1.38	0.86	-2.60	-1.18	-0.53
Dish Detergent	0.80	-2.70	-2.05	0.11	3.43	-1.77	-1.70	2.56	-1.06
Front-end Candies	-1.60	-1.07	0.17	4.17	-1.44	-0.67	-0.79	-1.23	-0.78
Frozen Dinners	-8.29	-8.87	3.06	-10.72	1.47	-6.47	6.21	-11.02	-8.95
Frozen Entrees	-16.68	23.80	-16.95	-16.63	-13.35	-15.19	-19.50	-14.70	-14.58
Frozen Juices	8.47	1.94	4.55	-0.10	6.47	-1.03	-6.13	3.53	0.68
Fabric Softeners	-0.85	-1.32	-0.12	-1.29	0.24	-0.21	-2.43	-1.17	-1.84
Grooming Products	0.10	0.43	-0.57	-0.34	-0.25	-0.68	-1.00	-0.09	-0.65
Laundry Detergents	0.26	-1.13	-1.45	-4.06	-1.22	6.66	-5.89	-0.79	-4.73
Oatmeal	4.29	-2.23	-1.84	4.33	-0.10	1.14	-1.37	-1.93	-0.33
Paper Towels	0.69	1.06	2.40	-0.41	3.70	-1.67	-0.24	-2.28	-1.57
Refrigerated Juices	6.32	-2.79	7.28	2.80	2.79	2.03	-7.90	-1.84	-1.99
Soft Drinks	-4.48	2.30	4.23	3.03	0.65	2.12	-4.90	0.10	4.83
Shampoos	-0.02	-1.08	-0.12	-1.69	0.89	-0.08	-1.60	-1.53	-1.09
Snack Crackers	-0.12	7.76	1.15	4.00	1.42	5.90	3.58	1.44	10.26
Soaps	0.77	0.40	-0.48	-0.32	2.68	1.24	-0.28	0.71	1.04
Toothbrushes	3.06	-3.20	-0.82	-0.32	0.11	-1.22	-2.51	-0.15	-2.32
Canned Tuna	-7.17	-5.29	-6.19	-4.03	-5.31	-6.54	-6.33	-4.57	-6.55
Toothpastes	-1.62	2.30	2.11	1.30	-0.91	-0.50	-0.77	-0.72	-1.84
Bathroom Tissues	-1.99	-7.95	-7.64	-5.67	1.94	-7.74	-9.97	-6.20	-9.75
ALL	-1.87	1.55	0.71	-0.43	0.47	0.33	-4.01	-0.88	-0.58

Table A.8. Price Decrease Ratio by Category and by Holiday

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas	No Holiday
Analgesics	11.46	12.72	18.58	14.45	8.35	12.52	11.89	14.90	9.85	18.84
Bath Soap	7.21	8.83	25.25	7.44	10.10	6.94	11.40	5.74	14.55	19.73
Beer	12.31	15.69	11.14	14.93	15.12	14.98	13.46	11.71	11.98	13.01
Bottled Juices	6.00	14.21	10.97	13.20	23.72	9.58	2.98	5.48	7.82	13.48
Cereals	7.22	16.70	16.66	14.24	17.92	13.79	9.63	19.50	15.08	14.92
Cheeses	11.27	12.15	12.00	11.54	9.91	19.58	12.37	14.09	14.81	12.61
Cookies	13.41	14.01	13.69	21.15	30.77	15.25	7.08	15.88	9.16	23.70
Crackers	11.75	5.57	6.20	6.99	26.39	6.89	8.15	7.85	5.91	17.14
Canned Soup	6.49	2.05	4.20	5.86	17.20	14.78	6.37	8.45	11.47	14.26
Dish Detergent	13.61	5.73	8.22	16.44	22.69	5.71	6.48	19.21	8.23	11.75
Front-end Candies	5.70	6.35	14.44	23.85	7.07	16.67	17.68	8.31	7.14	13.52
Frozen Dinners	13.95	10.35	29.43	9.64	25.19	14.88	27.98	6.83	17.03	27.04
Frozen Entrees	12.01	44.65	15.21	15.42	21.83	17.69	4.03	17.99	31.60	36.91
Frozen Juices	31.68	15.49	25.07	20.67	27.04	20.60	10.20	23.59	19.74	21.43
Fabric Softeners	7.64	9.42	15.09	6.51	12.38	9.97	7.32	9.61	9.09	9.95
Grooming Products	11.72	8.23	13.69	13.48	18.88	9.58	10.88	13.96	9.34	11.20
Laundry Detergents	13.34	13.95	14.65	8.21	17.24	27.02	4.37	19.18	7.57	14.15
Oatmeal	16.42		11.65	35.49	5.93	12.08	4.17	1.98	7.94	6.49
Paper Towels	7.49	9.63	13.01	7.59	15.34	5.36	11.28	3.66	6.79	8.77
Refrigerated Juices	24.22	16.40	27.08	23.47	24.28	22.12	12.56	14.88	17.12	19.18
Soft Drinks	19.41	25.76	24.47	25.74	23.57	27.09	24.59	25.81	27.54	25.73
Shampoos	18.64	15.10	17.66	12.09	18.79	20.64	18.84	16.47	15.50	18.96
Snack Crackers	9.02	22.04	11.46	16.23	12.98	14.61	11.88	12.66	18.05	9.38
Soaps	8.51	9.34	7.94	7.50	16.87	9.04	8.28	8.56	13.31	8.60
Toothbrushes	23.92	13.19	24.20	18.32	14.73	11.93	13.33	20.63	12.35	20.40
Canned Tuna	5.46	8.03	6.18	11.72	10.85	5.12	7.17	8.20	6.94	20.50
Toothpastes	10.11	26.22	22.81	15.52	12.99	17.83	16.43	13.66	9.54	16.65
Bathroom Tissues	13.67	7.86	12.32	14.42	19.61	7.03	3.91	10.38	3.69	18.84
ALL	15.58	21.11	19.36	18.26	20.65	19.50	14.47	17.34	17.93	19.91

Table A.9. Price Decrease Ratio Deviations from No-Holiday by Category

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas
Analgesics	-7.38	-6.13	-0.27	-4.39	-10.49	-6.32	-6.95	-3.95	-8.99
Bath Soap	-12.52	-10.90	5.52	-12.30	-9.63	-12.80	-8.33	-14.00	-5.18
Beer	-0.69	2.68	-1.86	1.92	2.11	1.97	0.46	-1.30	-1.03
Bottled Juices	-7.48	0.73	-2.51	-0.27	10.24	-3.90	-10.50	-8.00	-5.66
Cereals	-7.70	1.78	1.74	-0.68	3.01	-1.13	-5.29	4.58	0.16
Cheeses	-1.34	-0.46	-0.60	-1.06	-2.69	6.98	-0.23	1.49	2.21
Cookies	-10.30	-9.69	-10.01	-2.55	7.07	-8.45	-16.62	-7.82	-14.54
Crackers	-5.40	-11.57	-10.95	-10.16	9.24	-10.25	-9.00	-9.30	-11.23
Canned Soup	-7.77	-12.20	-10.05	-8.40	2.94	0.53	-7.89	-5.81	-2.79
Dish Detergent	1.87	-6.02	-3.53	4.69	10.95	-6.04	-5.27	7.46	-3.52
Front-end Candies	-7.82	-7.17	0.92	10.33	-6.45	3.15	4.16	-5.21	-6.38
Frozen Dinners	-13.10	-16.69	2.39	-17.40	-1.85	-12.16	0.94	-20.21	-10.01
Frozen Entrees	-24.90	7.74	-21.70	-21.49	-15.08	-19.22	-32.88	-18.92	-5.31
Frozen Juices	10.25	-5.94	3.64	-0.76	5.61	-0.83	-11.23	2.16	-1.69
Fabric Softeners	-2.31	-0.53	5.14	-3.43	2.43	0.02	-2.63	-0.34	-0.86
Grooming Products	0.52	-2.97	2.49	2.28	7.68	-1.63	-0.32	2.76	-1.86
Laundry Detergents	-0.81	-0.20	0.50	-5.94	3.08	12.86	-9.79	5.03	-6.58
Oatmeal	9.93	-6.49	5.17	29.00	-0.55	5.59	-2.31	-4.51	1.45
Paper Towels	-1.28	0.86	4.24	-1.18	6.56	-3.41	2.51	-5.11	-1.98
Refrigerated Juices	5.04	-2.78	7.90	4.29	5.10	2.93	-6.63	-4.30	-2.06
Soft Drinks	-6.32	0.02	-1.27	0.00	-2.17	1.35	-1.14	0.07	1.80
Shampoos	-0.32	-3.86	-1.30	-6.87	-0.17	1.68	-0.12	-2.49	-3.46
Snack Crackers	-0.36	12.66	2.08	6.85	3.60	5.23	2.50	3.29	8.67
Soaps	-0.09	0.74	-0.66	-1.10	8.27	0.44	-0.32	-0.04	4.71
Toothbrushes	3.52	-7.21	3.80	-2.07	-5.67	-8.47	-7.06	0.23	-8.04
Canned Tuna	-15.04	-12.46	-14.31	-8.78	-9.64	-15.38	-13.32	-12.29	-13.55
Toothpastes	-6.54	9.56	6.16	-1.13	-3.66	1.18	-0.22	-2.99	-7.11
Bathroom Tissues	-5.17	-10.98	-6.52	-4.42	0.77	-11.81	-14.93	-8.46	-15.15
ALL	-4.33	1.21	-0.55	-1.65	0.74	-0.41	-5.44	-2.57	-1.98

Table A.10. Number of Promoted Items by Category and by Holiday

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas	No Holiday
Analgesics	3.73	3.07	2.97	2.36	6.61	4.33	3.20	4.08	3.86	3.98
Bath Soap	1.44	3.40	1.24	2.35	1.69	3.38	1.13	0.57	1.18	1.81
Beer	14.38	28.03	25.94	21.12	19.33	20.45	21.62	18.67	24.19	18.77
Bottled Juices	19.09	28.60	26.98	23.18	24.11	24.19	13.92	24.40	28.80	24.62
Cereals	12.69	11.30	6.82	31.87	6.32	15.39	5.39	28.73	8.27	9.13
Cheeses	34.33	40.43	30.86	49.02	34.44	47.08	41.59	52.49	65.07	33.15
Cookies	45.54	39.87	25.81	35.70	30.36	31.93	14.55	39.76	16.63	32.98
Crackers	8.18	17.50	11.15	15.63	8.56	13.16	11.54	16.47	11.22	8.88
Canned Soup	21.60	6.82	7.66	15.18	27.26	22.86	13.38	26.00	26.68	21.17
Dish Detergent	7.44	4.99	6.66	5.89	7.33	8.91	9.71	6.15	10.61	7.42
Front-end Candies	4.40	9.94	10.27	13.30	4.05	5.81	5.65	4.84	12.77	8.49
Frozen Dinners	10.11	13.37	16.36	8.65	19.15	22.70	16.32	14.72	10.05	13.21
Frozen Entrees	20.29	36.87	13.18	18.42	29.48	29.30	7.65	25.49	17.74	27.37
Frozen Juices	13.01	16.91	13.97	12.36	13.23	7.05	8.66	11.15	14.41	10.61
Fabric Softeners	8.42	7.06	5.56	10.46	8.89	9.25	4.69	5.12	5.61	8.85
Grooming Products	21.32	24.38	5.74	8.55	7.07	8.68	5.08	11.69	8.42	13.94
Laundry Detergents	12.09	18.27	13.86	15.24	12.12	13.18	11.89	8.51	11.06	14.98
Oatmeal	6.26	0.00	1.66	3.12	7.71	5.78	4.18	1.13	5.32	6.30
Paper Towels	8.94	6.69	4.64	5.54	4.22	5.75	4.48	4.90	4.90	5.68
Refrigerated Juices	17.88	15.72	14.02	14.87	16.06	15.06	10.65	19.37	16.54	14.56
Soft Drinks	53.15	59.50	82.34	53.18	70.28	63.74	61.82	59.12	86.08	59.46
Shampoos	22.63	21.68	24.14	13.56	30.67	23.03	17.49	17.23	18.86	28.32
Snack Crackers	13.83	21.83	20.20	24.67	15.75	25.92	26.37	18.50	32.89	17.45
Soaps	14.91	9.64	7.74	12.97	10.18	13.76	9.28	8.34	8.54	10.82
Toothbrushes	8.91	1.34	3.31	5.93	6.69	6.92	3.76	6.37	4.90	5.80
Canned Tuna	7.34	14.72	14.69	14.17	9.66	17.19	12.93	19.15	11.15	10.39
Toothpastes	8.03	6.99	6.35	9.34	5.80	7.08	7.19	9.80	7.46	8.22
Bathroom Tissues	9.32	7.24	5.13	5.17	8.29	7.69	6.76	8.63	8.81	7.30
TOTAL	429.27	476.17	409.25	451.78	445.30	479.55	360.86	471.40	482.04	433.63

Table A.11. Number of Promoted Items' Deviations from No-Holiday by Category

	President	Memorial	July 4th	Labor	Halloween	Thanks	Post-Thx	Easter	Christmas
Analgesics	-0.25	-0.91	-1.01	-1.62	2.63	0.35	-0.78	0.10	-0.12
Bath Soap	-0.37	1.59	-0.57	0.53	-0.12	1.57	-0.68	-1.24	-0.63
Beer	-4.38	9.27	7.17	2.35	0.56	1.69	2.85	-0.09	5.42
Bottled Juices	-5.53	3.98	2.36	-1.44	-0.51	-0.43	-10.70	-0.22	4.18
Cereals	3.56	2.17	-2.30	22.75	-2.80	6.27	-3.73	19.60	-0.86
Cheeses	1.18	7.28	-2.28	15.87	1.29	13.93	8.44	19.34	31.92
Cookies	12.56	6.89	-7.16	2.72	-2.61	-1.05	-18.43	6.79	-16.35
Crackers	-0.70	8.62	2.27	6.75	-0.32	4.27	2.66	7.59	2.34
Canned Soup	0.43	-14.34	-13.50	-5.98	6.10	1.69	-7.79	4.83	5.51
Dish Detergent	0.02	-2.43	-0.76	-1.53	-0.09	1.49	2.28	-1.27	3.19
Front-end Candies	-4.08	1.46	1.78	4.81	-4.44	-2.67	-2.83	-3.65	4.28
Frozen Dinners	-3.10	0.16	3.15	-4.57	5.93	9.49	3.11	1.51	-3.16
Frozen Entrees	-7.08	9.50	-14.18	-8.95	2.12	1.93	-19.72	-1.87	-9.63
Frozen Juices	2.40	6.30	3.36	1.75	2.62	-3.56	-1.96	0.54	3.80
Fabric Softeners	-0.43	-1.80	-3.30	1.61	0.04	0.40	-4.16	-3.73	-3.24
Grooming Products	7.38	10.44	-8.20	-5.39	-6.87	-5.26	-8.86	-2.25	-5.52
Laundry Detergents	-2.88	3.29	-1.11	0.26	-2.85	-1.80	-3.09	-6.47	-3.92
Oatmeal	-0.04	-6.30	-4.64	-3.18	1.41	-0.51	-2.12	-5.17	-0.98
Paper Towels	3.26	1.01	-1.04	-0.14	-1.46	0.08	-1.19	-0.78	-0.77
Refrigerated Juices	3.32	1.16	-0.54	0.31	1.50	0.50	-3.91	4.81	1.98
Soft Drinks	-6.31	0.04	22.87	-6.28	10.82	4.27	2.36	-0.35	26.62
Shampoos	-5.69	-6.64	-4.17	-14.76	2.35	-5.29	-10.83	-11.09	-9.45
Snack Crackers	-3.62	4.38	2.75	7.22	-1.70	8.47	8.92	1.06	15.44
Soaps	4.09	-1.18	-3.08	2.15	-0.64	2.93	-1.54	-2.48	-2.28
Toothbrushes	3.11	-4.46	-2.49	0.13	0.89	1.12	-2.04	0.57	-0.90
Canned Tuna	-3.04	4.34	4.31	3.79	-0.73	6.81	2.54	8.76	0.76
Toothpastes	-0.18	-1.23	-1.87	1.12	-2.42	-1.14	-1.03	1.58	-0.76
Bathroom Tissues	2.02	-0.06	-2.17	-2.13	0.99	0.39	-0.55	1.33	1.51
TOTAL	-4.35	42.54	-24.37	18.16	11.68	45.92	-72.77	37.77	48.41

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